

Systematic Review

The Determinants of Success in One Day International (ODI) and Twenty20 (T20) Cricket Matches: A Systematic Review and Meta-Analysis

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Abstract

Understanding the determinants of success in International One Day (ODI) and Twenty20 (T20) cricket is essential for optimising team and player performance. This review aimed to identify the key performance indicators (KPIs) associated with successful outcomes in elite international ODI and T20 matches. The review also examines performance analysis (PA) methods and trends across male and female cricketers. Comprehensive searches were conducted across PubMed, SPORTDiscus, IEEE Xplore, ACM Digital library, Ebscohost and Web of Science, covering literature published between 2000 and the present. Studies were included if they reported on KPIs or PA techniques contributing to the success in cricket. Following a rigorous screening process, nine studies met the inclusion criteria. This review revealed that most PA studies focused on distinguishing KPIs between winning and losing teams. Although video technology and statistical models are increasingly applied, relatively few investigations have incorporated contextual variables or gender-inclusive perspectives. Notably, only one study examined female cricketers, which limited the ability to draw strong conclusions on sex-specific performance differences. Furthermore, gaps remain regarding the consistent application of PA methods across formats. This review provides an overview of success determinants in international cricket and highlights the need for holistic, inclusive and ecologically valid approaches.

Keywords: cricket; performance analysis; key performance indicators; match success; tactical performance



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1. Introduction

The limited overs formats in cricket, particularly in One Day Internationals (ODIs) and Twenty20 (T20), have transformed the sport into a fast-paced, commercially lucrative spectacle where success is determined by fine tactical margins [1,2]. With significant investment in these formats, performance analysis has become central to informing coaches, analysts and franchise owners about the strategies and technical skills linked to winning

outcomes [3–8]. In both ODI and T20 cricket, where the margin for error is minimal and decision-making under pressure is critical [9–11], understanding the key performance indicators (KPIs) that distinguish winning from losing teams is essential.

Cricket performance is traditionally assessed across batting, bowling and fielding domains [12–16]. Cricket performance analysis, particularly biomechanical analysis, has provided insights into technique refinement, such as bat lift angles [13–15], optimal bowling action [17] and fielding mechanics, including throwing accuracy and speed [18]. Match outcomes are often more directly influenced by technical execution (e.g., yorker accuracy and boundary conversion rate) and tactical decision-making (e.g., bowling changes and strike rotation) [19–22]. Technical KPIs, such as run rate management, powerplay utilisation and death-over wicket-taking, reflect strategic effectiveness. Match statistics and notational analysis have long been used to guide tactical decision-making in sport [23], including cricket-specific tactics, such as team selection, bowling strategy and field placements [10,24–28]. Studies have demonstrated that optimal line-and-length bowling choices, target scoring zones and situational bowling variations can shift momentum and influence match outcomes [29]. Modern technologies, such as ball-tracking and advanced analytics, have further enabled detailed tactical profiling, thereby integrating variables like batsman-bowler matchups, handedness and venue-specific trends [30].

Despite the maturity of the ODI and T20 formats, research into cricket KPIs has largely prioritised isolated statistical measures over contextual tactical insights [9,29,31,32]. Previous studies in men's ODI and T20 cricket have highlighted variables such as run rate, total wickets and death-over performance as important, but have not consistently linked these to in-game tactical decision-making or coaching applications. Moreover, female cricket remains significantly under-researched, and few studies explore how KPIs differ across performance levels, formats or playing conditions. Adopting a broader range of KPI options in other sports has demonstrated the value of integrating multiple indicators to capture performance complexity [33–35], yet such holistic approaches are rarely applied in cricket.

This systematic review addresses these gaps by synthesising the KPIs associated with success in international ODI and T20 cricket, with particular emphasis on technical and tactical indicators. The objectives of the review were to (i) identify and describe the KPIs used in International ODI and T20 cricket matches, (ii) determine the methods used in performance analysis in International ODI and T20 cricket matches and (iii) analyse the cricket performances of elite male and female cricket players. In doing so, it offers a contextualised understanding of how KPIs can inform tactical decision-making and coaching strategy in high-performance cricket.

2. Materials and Methods

This systematic review was performed in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement [36] and the PRISMA-P checklist [37]. The outcomes for each step of PRISMA are summarised in the flow diagram (Figure 1). Details of full protocol registration for this systematic review may be found on the Open Science Framework (protocol reference: 10.17605/OSF.IO/HGE4J).

2.1. Summary of the Methods

All study types and designs were included and appraised accordingly. The inclusion criteria were defined using the Condition, Context and Population (CoCoPop) mnemonic for systematic reviews of prevalence and descriptive studies [38]. Using the CoCoPop frameworks: Condition (Co): Performance indicators associated with match success in ODI and T20 cricket; Context (Co): All match play in international, provincial or high-

performance cricket environments and Population (Pop): All cricket players (male and female) of any age competing at the levels stated above. Exclusion criteria included (i) studies focusing on other outcome measures as the main exposures; (ii) systematic reviews or other types of reviews, opinion pieces, letters and editorials; (iii) experimental interventions; (iv) studies that were non-English. Only English language studies were included due to the primary focus on literature published in major international sport science journals, which predominantly publish in English. Additionally, translation resources were not available, and the tactical and technical terminology used in cricket performance analysis would risk misinterpretation if translated without subject expertise. We acknowledge that this may have excluded potentially relevant studies and could have influenced the comprehensiveness of the evidence synthesis.

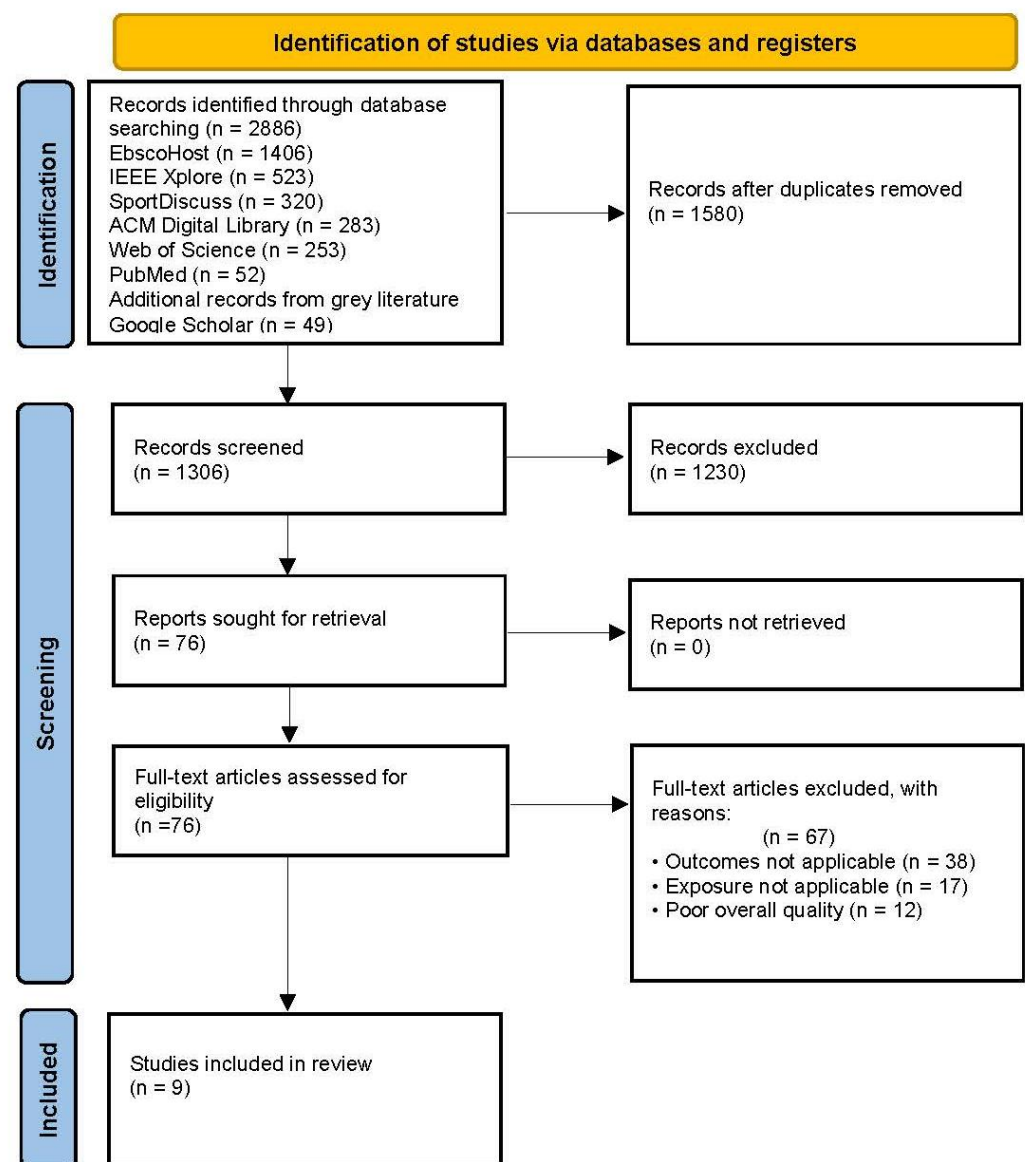


Figure 1. PRISMA flow diagram summarising the search process.

2.2. Search Strategy

A detailed literature search was conducted by the two primary reviewers (RVN and JR) for identifying studies, extracting data, verifying data and grading the quality of results. RVN was the principal investigator tasked with data analysis, narratively synthesising

the data and writing up the systematic review. A third reviewer (LL) was tasked with adjudicating and resolving any disagreement between the two independent reviewers.

2.3. Electronic Literature Search

The search strategy was developed iteratively to capture studies on match-play performance analysis in ODI and T20 cricket. Keywords were identified from prior systematic reviews and refined through pilot searches to ensure sensitivity (capturing all potentially relevant records) and specificity (minimising irrelevant records). By evaluating search phrases used in past systematic reviews on performance analysis, a comprehensive search strategy or string was established [39,40]. The following six electronic databases were searched: PubMed, SPORTDiscus, IEEE Xplore, ACM Digital library, Ebscohost and Web of Science, with publication year from 2000 to present. Keywords were used in various arrangements depending on the specific database. In Table 1, the Boolean structure was informed by a scoping search to identify the most common terminology used in cricket and sport performance research. This allows for a balance in sensitivity (retrieving a wide range of KPI-related literature) with specificity (excluding irrelevant domains, such as fitness, biomechanics or injury studies). The strategy was implemented in three phases:

1. Phase 1—Scoping Search: Broad terms (e.g., “performance analysis”, “game analysis”, “sports analytics”, “key performance indicators”) were in SPORTDiscus to explore the terminology and indexing used in relevant studies. Synonyms, British/American spellings and plural forms were noted.
2. Phase 2—Comprehensive Database Search: A structured Boolean string combined three keyword groups:
 - Performance analysis terms (e.g., “performance analysis”, “game analysis”, “tactical analysis”, “sports analytics”, “key performance indicators”), joined with OR to capture all variations.
 - Cricket teams (e.g., “cricket”, “cricket sport” joined with AND to restrict results to cricket-specific literature.
 - Exclusion terms (e.g., “injury”, “fitness”, “biomechanics”), joined with NOT to remove high-volume irrelevant literature. A similar approach was applied in previous work [39–41] and adapted here for the current review.
3. Phase 3—Supplementary Search: Reference lists of included studies were hand searched, while forward citation tracking was conducted in Google scholar, and grey literature sources were searched using a simplified keyword set (“cricket” AND “performance indicators”)

Table 1. Concise Boolean search strategy.

Keyword Group	Examples	Boolean Operator	Purpose
Performance analysis terms	“performance analysis”, “match analysis”, “key performance indicators”	OR	Capture all performance/KPI studies
Cricket terms	“cricket”, “cricket sport”	AND	Limit to cricket
Exclusion terms	“injury”, “fitness”, “biomechanics”	NOT	Remove irrelevant studies

This approach maximised the retrieval of relevant KPI focused cricket studies while minimising irrelevant results. The full database-specific search strings are found in Supplementary Material (Supplementary S1).

2.4. Additional Searches for Grey Literature

The search strategy was completed by searching the following databases for grey literature. Grey literature was included to minimise publication bias and capture potentially unpublished but relevant work. Google Scholar and the Networked Digital Library of theses and dissertations were systematically searched using the same Boolean structure, with the first 200 results screened for relevance. RVN and JR also searched the reference lists of selected articles to identify relevant articles meeting the inclusion criteria.

2.5. Selection of Studies

All studies, as full-text articles, that met the inclusion criteria were selected for screening. Thereafter, the full-text articles were assessed independently by two reviewers (RVN and JR) using the Rayyan[®] intelligent systematic review (RIS) tool [42]. When screening the studies, three categories were used, namely, included, excluded and unsure. Any uncertainties regarding study inclusion were discussed between the two reviewers. In the event of disagreement, a discussion was held with the third reviewer (LL) and resolved by the latter.

2.6. Steps Involved in the Selection and Screening of Studies

The following steps were involved in the literature search:

1. The selection and screening process followed a structured sequence. First, pre-selected databases were searched systematically, identifying and screening titles and abstracts of potential studies for eligibility.
2. Compiling search outputs into a reference software, namely, EndNote X9, Clarivate Analytics.
3. Removing duplicates.
4. Screening full-text articles against the inclusion criteria using Rayyan Systems Inc.
5. Final decisions on study inclusion were made after independent review and consensus among the research team.
6. Extracting data from the included studies using a data extraction form.

2.7. Data Extraction and Data Management

To extract study-level information, we used a researcher-designed extraction form (Supplementary S2 and S3). This approach, adapted from previous studies Ras et al. [41], enabled consistency across two reviewers (RVN and JR) to extract and capture the key characteristics of each study. The information extracted was author(s), date of study publication, study title, study design and country, the context (professional cricket environment, i.e., professional teams, schools or club-level cricket), sampling method and sample size, details of the participants (number of participants, age and gender) and outcome measures.

All KPIs reported in the included studies were extracted; however, emphasis in the synthesis was placed on indicators that were (i) reported by multiple independent studies, and (ii) demonstrated a statistically significant association with match outcomes (e.g., variable importance scores). Where different studies used comparable, but non-identical, measures, they were grouped under a common construct to enable synthesis. Where KPIs appeared in only one study, without a statistical association to match the successor, and when they lacked contextual relevance to on-field performance, they were recorded but not prioritised in the narrative synthesis. This approach ensured that the final set of prioritised KPIs reflected the most consistent and empirically supported performance indicators in elite cricket.

2.8. Critical Appraisal of Included Studies

The tool used to assess the methodological quality of the cross-sectional and observational studies was Strengthening of Reporting of Observational Studies in Epidemiology (STROBE) [43], which was previously used in systematic reviews on performance analysis in sport [40]. The appraisal focused on methodological transparency, statistical reporting and relevance to the research aims. The original 22-item STROBE checklist was used, and a recommendation was developed to provide practical, domain-specific guidance for each STROBE item in the context of cricket performance analysis. These recommendations were adapted from the original STROBE guidance [43] and were informed by how a prior study in sport science had applied STROBE [40]. Where necessary, the authors customised the recommendations to reflect cricket-specific methodological considerations, such as defining KPIs, contextualising match variables and identifying performance indicators. Each study was appraised using the STROBE checklist, focusing on methodological transparency, statistical reporting and applicability to the research aim.

Questions in STROBE were answered dichotomously. Each question answered “yes” received a “1”, while each “no” earned a “0”. No provision was made for unsure decisions (there were none). Each study was scored against the 22-item STROBE checklist, with a maximum score of 22. Thresholds used for quality categories were: high quality: $\geq 80\%$ of total score; moderate quality: 50–79% and low quality: $<50\%$ [43]. This threshold was selected to ensure methodical transparency and robustness of included evidence. Inter-rater reliability for STROBE scoring between the two reviewers was calculated using Cohen’s Kappa (k), yielding a value of $k = 0.82$, indicating strong agreement. Disagreements were resolved by discussion and, when necessary, adjudication by the third reviewer (LL).

2.9. Data Analysis

Where data were sufficiently homogenous, in terms of design, population and outcome measures, a meta-analysis was conducted to synthesise the quantitative findings. The primary outcome variables analysed were the batting and bowling key performance indicators. Data were extracted as means and standard deviations for continuous variables. Where studies reported insufficient data, the corresponding authors were contacted for input; if no response was received, those data were excluded from analysis but retained in the narrative evidence synthesis.

Meta-analyses were conducted using a random-effects model to account for between-study heterogeneity. Effect sizes were calculated as mean difference (MD) between intervention (winning team) and control (losing team) groups, with 95% confidence interval (CIs) included. Heterogeneity was assessed using the Cochran’s Q test ($p < 0.05$ indicating statistical significance and quantified with the I^2 statistic (values of 25%, 50% and 75% represented low, moderate and high heterogeneity, respectively). Forest plots were generated to display individual study estimates and the pooled effect size. Statistical analyses were performed using SPSS V29.

3. Results

3.1. Study Selection

The six electronic databases and additional grey literature yielded an initial total of 2886 publications, which included a large volume of duplicates, irrelevant formats (e.g., test cricket) and non-peer-reviewed literature (Figure 1). After removal of 1580 duplicates, 1306 studies remained and were screened using the title and abstract information, with 1230 studies excluded for being unrelated to KPI analysis in ODI or T20 cricket. Of the 76 studies that remained for full-text screening, 67 were excluded for the following reasons: (1) outcomes not applicable, not reporting KPI data ($n = 38$), (2) exposure not applicable

($n = 17$) and (3) poor overall quality ($n = 19$). A total of nine studies were included and proceeded to data extraction.

3.2. Study Characteristics

The included studies encompassed nine cross-sectional/observational studies conducted between 2008 and 2022 [9,10,22,29,31,32,44–46]. Studies were conducted in different countries with different world rankings, based on the shorter cricket formats (ODI and T20): India (1st in both), Australia (2nd in both), South Africa (4th and 6th, respectively), New Zealand (5th in both), United Kingdom (7th and 10th, respectively) and West Indies (10th and 4th, respectively). A summary of the included studies is given in Table 2.

3.3. Year of Publication

The nine included studies spanned the period 2008–2022, revealing an evolution in KPI focus over time. Earlier research (2008–2012) primarily examined broad indicators of cricket performance, such as runs, total wickets taken and general partnerships, reflecting the prevailing descriptive match-analysis approach used in earlier research. Mid-period studies (2014–2017) began incorporating more situational KPIs, such as phase-specific run rates and wickets taken in powerplays, aligning with the tactical demands of limited overs cricket. The most recent study (2022) emphasised advanced performance indicators, like boundary efficiency (balls per boundary) and rapid early wicket-taking, consistent with the increasing influence of T20 cricket strategies on performance analysis. This progression suggested a methodological shift from static, outcome-focused measures previously used to dynamic, context-dependent indicators currently used that more directly inform targeted training interventions.

3.4. Sample Size

The sample size for each of the studies ranged from seven matches to 400 innings (Table 2). The matches included ODIs ($n = 2$) and T20 ($n = 7$), divided into T20 World Cup tournaments ($n = 2$) and T20 domestic competitions ($n = 5$). The studies varied geographically between the northern (United Kingdom, India and Sri Lanka) ($n = 6$) and southern (Australia, New Zealand and South Africa) ($n = 3$) hemispheres. The studies focused mostly on male professional cricket ($n = 9$), with one study on female cricket ($n = 1$).

3.5. Performance Indicators

A total of 234 performance indicators were identified across the nine reviewed articles (Table 2). Only 22.2% ($n = 2$) of studies provided full definitions of variables used in the analyses, such as match outcome and pitch location. All included studies examined professional or elite-level cricket, with most focusing on men's matches. As such, the KPIs reported in the current study reflect high-performance competition and may not directly represent amateur or youth-level competition.

The KPIs linked to successful performance are shown in Table 2. In T20 cricket, successful batting performance was characterised by a higher run rate during the middle overs (7–16) and the final three overs (17–20), a greater proportion of runs scored from boundaries, especially fours, and building partnerships of 50 runs or more [22,31]. Boundary efficiency (fewer balls per boundary) was a leading performance driver for both men's and women's competitions. T20 men's teams tended to gain more from early breakthroughs (dismissing the top three batters quickly), whereas women's teams benefited more from sustained innings, reflected in the higher number of balls faced and the strong middle-over scoring rates.

Table 2. Study characteristics of included studies.

References	Sample Size	Competition Level	Format	Gender	Significant KPIs	Main Outcomes
Bhardwaj & Dwyer, [31]	200 matches for males and 90 for females	Domestic Australia Big Bash League (BBL) and Women’s Big Bash League (WBBL)	T20	Male and Female	Batting: Run rate in overs 7th–16th, Run rate in overs 17th–20th, Boundaries scored in 4’s, Balls per boundary. Bowling: Time to first 3–5 wickets.	Higher middle and death-over run rate, more boundaries. However, in men’s T20 dismissing the top three opposition batters quickly was stronger predictors of success than in women’s T20. In women’s T20, balls faced played a larger role, suggesting an emphasis on sustained innings building in addition to boundary scoring
Douglas & Tam, [9]	27 Matches	International ICC World Cup 2009	T20	Male	Batting: Fewer wickets lost during the powerplay, higher overall run rate, higher run-rate in the middle overs (overs 7–14). Bowling: Fewer wickets lost, more dot balls bowled.	Winning teams protected wickets, early maintained higher run rates throughout and applied bowling pressure through dot balls
Irvine & Kennedy, [10]	40 Matches	International ICC World Cup from 2012 to 2016	T20	Male	Batting: Innings run rate Bowling: Total number of dot balls bowled, total number of wickets taken.	Winning teams achieved higher innings run rates, bowled more dot balls and took more wickets compared to losing teams, indicating that sustained scoring momentum and bowling pressure were key determinants of match success.
Moore et al. [29]	7 Matches	Domestic: English first class	T20	Male	Batting: Percentage runs from boundaries Bowling: Taking more wickets overall, wickets taken in the last six overs.	Winning teams scored a greater share of runs through boundaries and took more wickets overall, particularly in the final six overs, applying late-innings bowling pressure.

Table 2. Cont.

References	Sample Size	Competition Level	Format	Gender	Significant KPIs	Main Outcomes
Najdan et al. [44]	29 Matches	Domestic English competition	T20	Male	Batting: 50+ run partnerships, Individual batsman contributing 75+ runs, Individual batsman contributing 50–75 runs Bowling: Losing fewer wickets in the powerplay, losing fewer wickets in the 7th–10th overs	Match success was linked to strong top-order partnerships and major individual contributions, combined with preserving wickets during both the powerplay and early middle overs.
Petersen et al. [32]	56 Matches	Domestic IPL Tournament	T20	Male	Batting: Higher innings run rate Bowling: Taking more wickets overall, taking more wickets in the last six overs	Teams that maintained a higher run rate and struck regularly with the ball, especially in the closing overs, were more likely to win.
Scholes & Shafizadeh, [46]	17 Matches	Domestic Champions League	T20	Male	Fielding: Catch frequency inside the 30-yard circle, catch percentage outside the 30-yard circle	Superior catching efficiency in both close and deep fielding positions contributed to higher win probabilities.
Petersen et al. [45]	47 matches	International Cricket World Cup	ODI	Male	Batting: Higher innings run rate Bowling: Taking more wickets overall, taking more wickets in the last six overs	Winning teams combined sustained batting momentum with effective wicket-taking throughout the match, especially in the death overs.
Petersen, [22]	94 matches	International Cricket World Cup in 2007 and 2015	ODI	Male	Batting: Higher batting run rate, boundaries scored in 4 s, and the number of 50+ partnerships Bowling KPIs: Taking more wickets overall, maiden overs	Match wins were associated with faster scoring, frequent boundary hitting and strong partnerships, supported by consistent wicket-taking and pressure through maiden overs.

Abbreviations: ICC = International cricket council; IPL = Indian premier league; KPIs = Key performance indicators; ODI = One-day international.

Bowling trends differed subtly by format. In T20 matches, winning teams took more wickets overall, dismissed the first three to five batters more quickly, preserved wickets while batting, especially during the powerplay and in overs 7–10, and restricted scoring through dot balls [9,10,29,31,32,44]. In ODIs, wicket-taking remained crucial, particularly in the final six overs, with maiden overs contributing more strongly to success than in T20 cricket [22,45].

Fielding indicators in T20 included a higher catch frequency inside the 30-yard circle and a greater catch percentage outside it [46], whereas no equivalent strong fielding predictors were consistently observed in ODI analyses. Across both formats, while the direction of KPIs was broadly similar, their relative importance varied. Male competitions often showed a stronger influence of boundary-hitting efficiency and aggressive early wicket-taking. Female matches tended to place more emphasis on sustained partnerships, wicket preservation and consistent middle-over scoring. T20 cricket placed a greater premium on rapid scoring and early wickets, while ODIs rewarded sustained scoring pressure, disciplined bowling (including maidens) and the ability to accelerate in the closing overs.

To support practical application in coaching and performance analysis, the identified KPIs were further organised into three overarching categories (Table 3): technical/biomechanical, tactical decision-making and physical. This structure highlights not only the specific skills and match events associated with success, but also the underlying performance domains they reflect. Grouping KPIs in this way enables coaches, sport analysts and support staff to target training interventions more systematically, for example, refining technical execution for boundary efficiency, sharpening tactical choices around wicket-taking phases or building the physical capacity to sustain performance under match pressure.

3.6. Strengths and Weaknesses of the Studies

The strengths and weaknesses of the studies included in the review appear in Table 4 and are based on the STROBE checklist. Each study was scored against the 22-item STROBE checklist, with a maximum score of 22. Studies were classified as high ($\geq 80\%$), moderate (50–79%) or low quality ($<50\%$) based on the thresholds used in previous systematic reviews [42]. The rating of the studies ranged from 45 to 77%, with the majority scoring poorly in the methods and results sections, by failing to define the study/outcome variables, methods, results or report on the validity and reliability of the instruments employed.

3.7. Batting Performance Indicators

Figure 2 shows batting performance indicators. On average, the winning teams scored 25.94 more runs than the losing teams (pooled mean difference = 25.94; 95% CI: 8.91 to 42.98; $p < 0.001$). Heterogeneity indicated substantial variability across studies ($I^2 = 88\%$; Q-test $p < 0.001$), suggesting that the magnitude of the scoring advantage differed by tournament, match format and contextual factors, such as pitch conditions, opposition quality and match location. Due to this high heterogeneity, a random-effect model was applied, which accounts for between-study variability.

Table 3. Key performance indicators organised by performance domain for training and match analysis.

KPI Category	Example KPIs	Impact on Match Outcome
Technical/biomechanical	Boundary percentage runs, balls per boundary, batting accuracy, bowling accuracy, catching efficiency	Greater batting efficiency through boundary hitting increased scoring momentum; precise bowling created wicket-taking chances; superior catching, both close-in and deep, directly converted opportunities into dismissals.
Tactical decision-making	Higher middle and death-over run rates, early wicket-taking, partnerships, phase-specific focus	Timely acceleration in middle/death overs, protecting wickets in powerplay and striking in key phases (early breakthroughs in men’s T20, sustained innings in women’s T20) shifted match momentum toward winning teams.
Physical	Balls faced in sustained partnerships, stamina in long bowling spells, endurance in fielding	Ability to bat for extended periods (notably in women’s T20) and maintain pace/accuracy in later bowling overs enabled consistent pressure application across the match, especially in high-intensity closing phases.

Table 4. Cont.

Checklist	Item No.	Recommendation	Bhardwaj & Dwyer [31]	Douglas & Tam [9]	Irvine & Kennedy [10]	Moore et al. [29]	Najdan et al. [44]	Petersen et al. [32]	Scholes & Shafizadeh [46]	Petersen et al. [45]	Petersen [22]
Outcome data	15	(a) For cohort studies, report the number of outcome events or provide summary measures over time.	0	0	0	0	0	0	0	0	0
		(b) For case-control studies, report numbers in each exposure group or provide summary measures of exposure.	0	0	0	0	0	0	0	0	0
		(c) For cross-sectional studies, report the number of outcome events or summary measures.	0	0	0	0	0	0	0	0	0
Main results	16	(a) Present unadjusted and, if applicable, confounder-adjusted estimates with precision measures (e.g., 95% confidence interval). Indicate which confounders were adjusted for and why.	1	1	1	1	1	1	1	1	1
		(b) When continuous variables are categorised, provide the category boundaries.	1	1	1	1	1	1	1	1	1
		(c) If appropriate, translate relative risks into absolute risks for meaningful interpretation over time.	0	0	0	0	0	0	0	0	0
Other analyses	17	Describe any additional analyses conducted, including subgroup analyses, interaction effects, or sensitivity checks.	1	1	0	0	0	0	0	0	0
Key results	18	Provide a concise summary of the main findings, explicitly linking them to the stated objectives of the study.	1	1	1	1	1	1	1	1	1
Study Limitations	19	Critically reflect on study limitations, noting possible sources of bias such as small sample sizes, restricted match formats, or lack of contextual variables, and consider how these might have influenced the findings.	1	0	1	1	1	0	1	0	1
Interpretation of results	20	Offer a balanced interpretation of the findings, considering study objectives, methodological limitations, multiplicity of analyses, consistency with other studies, and the broader body of evidence.	1	1	1	1	1	0	1	1	1
Generalisability	21	Reflect on how applicable the findings are across different formats of cricket, player populations or competition levels.	0	0	0	0	1	0	0	0	0
Funding	22	Clearly state the funding source(s) that supported the research, and explain whether the funders had any involvement in the study design, data collection, analysis or interpretation of cricket performance outcomes.	0	0	0	0	0	0	0	0	0
Total score			15	14	15	13	17	10	14	12	15
Rating percent			68	63	68	59	77	45	63	54	68

Note: Recommendations were adapted from the original STROBE statement [42]. Where relevant, the authors customised the recommendation to reflect cricket-specific methodological considerations.

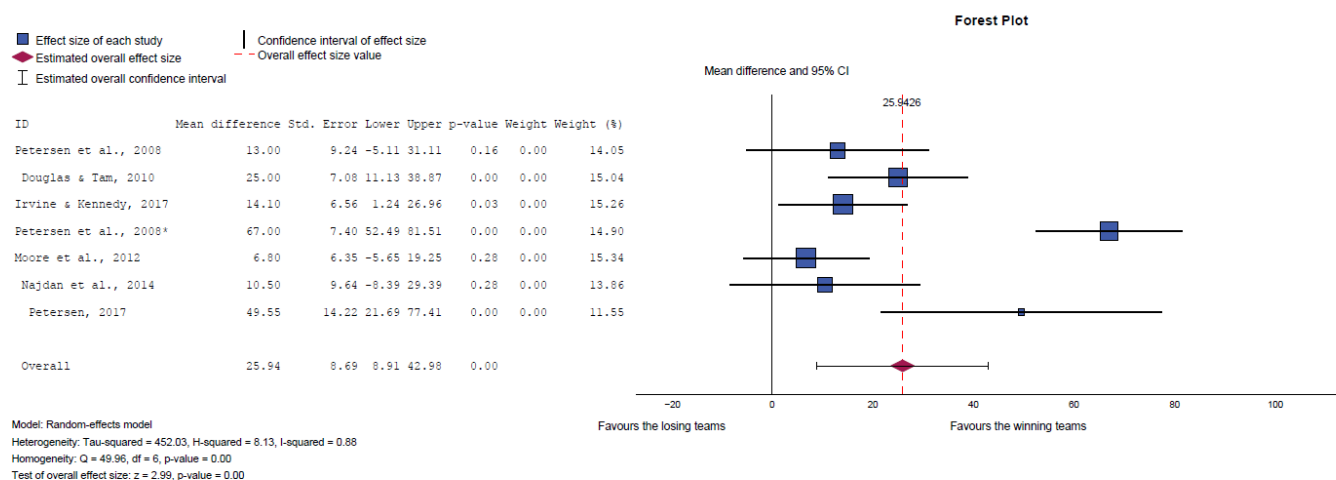


Figure 2. Forest plot of batting performance indicators [9,10,22,29,32,43,44].

Figure 3 shows the balls faced by the winning teams. On average, winning teams faced 4.51 fewer deliveries than losing teams (pooled mean difference = -4.51 ; 95% CI: -8.43 to -0.58 ; $p = 0.02$). The negative mean difference suggests that winning teams tended to complete their innings with fewer balls, which may reflect higher batting efficiency and more aggressive scoring rates. At the individual study level, the largest negative effect was observed by Irvine and Kennedy [10] (-12.90 balls, $p < 0.001$), and Moore et al. [29] (-4.5 balls, $p = 0.03$). Heterogeneity was from moderate to high ($I^2 = 70\%$; Q-test $p = 0.02$), suggesting that the effect varied across competitions and contexts.

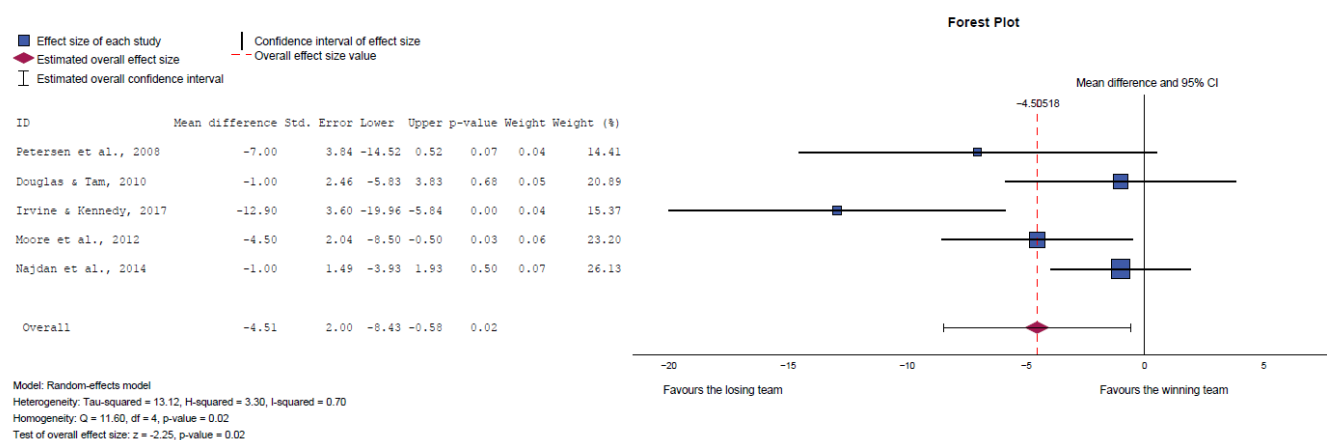


Figure 3. Forest plot of balls faced by the winning teams [9,10,29,32,43].

Figure 4 shows the run rates of winning teams. On average, winning teams scored 1.43 more runs per over than losing teams (pooled mean difference = 1.43 ; 95% CI: 1.06 to 1.79 ; $p < 0.001$). In practical terms, this equates to approximately 28 additional runs across a 20-over innings, which is often match-defining in the T20 format. All included studies reported a positive effect, with Petersen et al. [32], Douglas and Tam [9], Irvine and Kennedy [10] and Petersen et al. [45] displaying statistical significance. Moore et al. [29] reported a smaller, non-significant effect ($+0.50$ runs per over). Study weights were relatively balanced, with Petersen et al. [45] contributing the largest weight ($\sim 20.8\%$). Heterogeneity was moderate ($I^2 = 60\%$; Q-test $p = 0.04$).

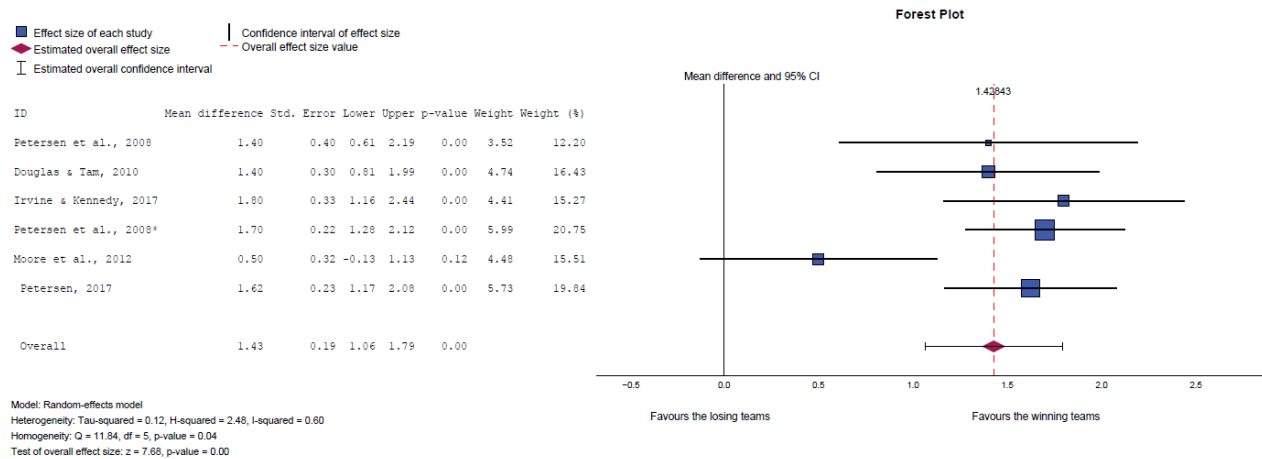


Figure 4. Forest plot of run rates scored by the winning teams [9,10,22,29,32,44].

Figure 5 displays the pooled analysis for sixes scored by winning teams. Winning teams hit significantly more sixes than losing teams, with a mean difference of 1.94 sixes (95% CI: 1.17 to 2.70; $p < 0.001$). Petersen et al. [45] reported +3.15, Petersen [22] reported +2.42, and Douglas and Tam [29] reported +1.60, with all results statistically significant. Others, including Moore et al. [29], Najdan et al. [44], also showed positive mean differences, albeit smaller in magnitude, and, in some cases, non-significant. Heterogeneity was low ($I^2 = 31\%$; Q-test $p = 0.24$).

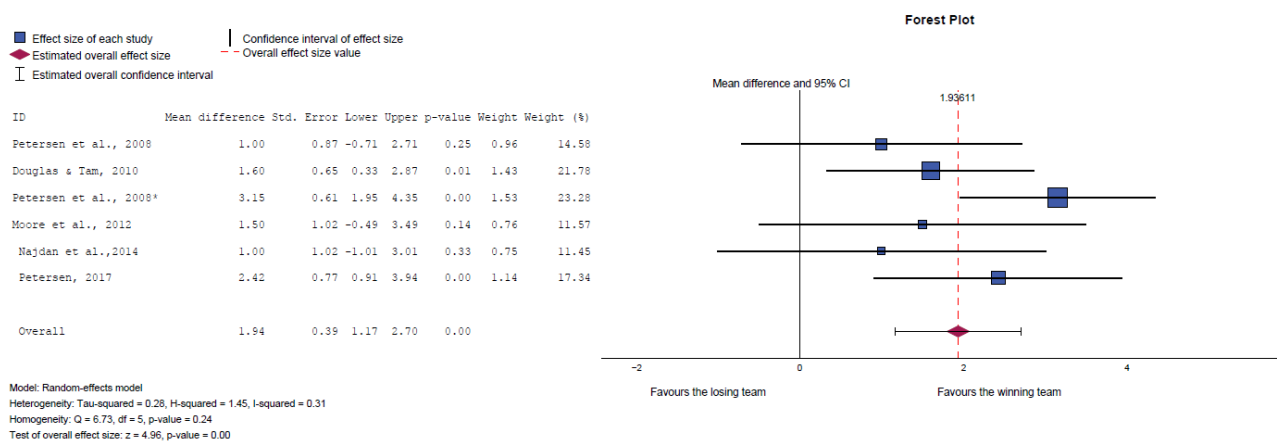


Figure 5. Forest plot of sixes scored by the winning teams [9,22,29,32,43,44].

Figure 6 displays the results for fours scored by winning teams. Winning teams scored 3.87 more fours than losing teams (95% CI: 2.22 to 5.52; $p < 0.001$). Douglas and Tam [9] reported +3.70, Petersen et al. [45] reported +6.00, and Petersen [22] reported +6.75, and all results were statistically significant. Other studies also showed positive mean differences, albeit smaller in magnitude. Heterogeneity was moderate ($I^2 = 62\%$; Q-test $p = 0.02$).

Figure 7 displays a pooled analysis of singles scored by the winning teams. There was no significant difference in the number of singles scored between winning and losing teams, with a mean difference of 0.15 (95% CI: -4.54 to 4.84; $p = 0.95$). This negligible positive effect suggested that strike rotation through singles occurred at a similar rate for both winning and losing teams. The results from the individual studies were mixed. Two studies [22,45] reported relatively large positive differences in favour of winning teams, with one being statistically significant ($p = 0.03$) and the other approaching significance ($p = 0.06$). In contrast, several studies showed small negative effects, indicating marginally

more singles scored by losing teams, though none of these differences were statistically significant. Heterogeneity was substantial ($I^2 = 69\%$, Q -test $p = 0.03$).

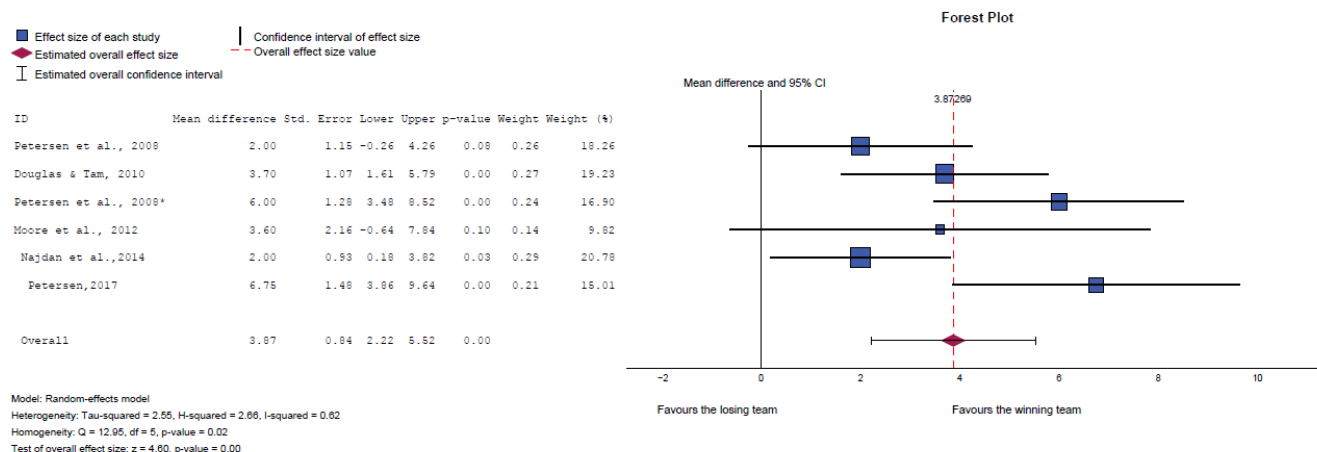


Figure 6. Forest plot of fours scored by the winning teams [9,22,29,32,43,44].

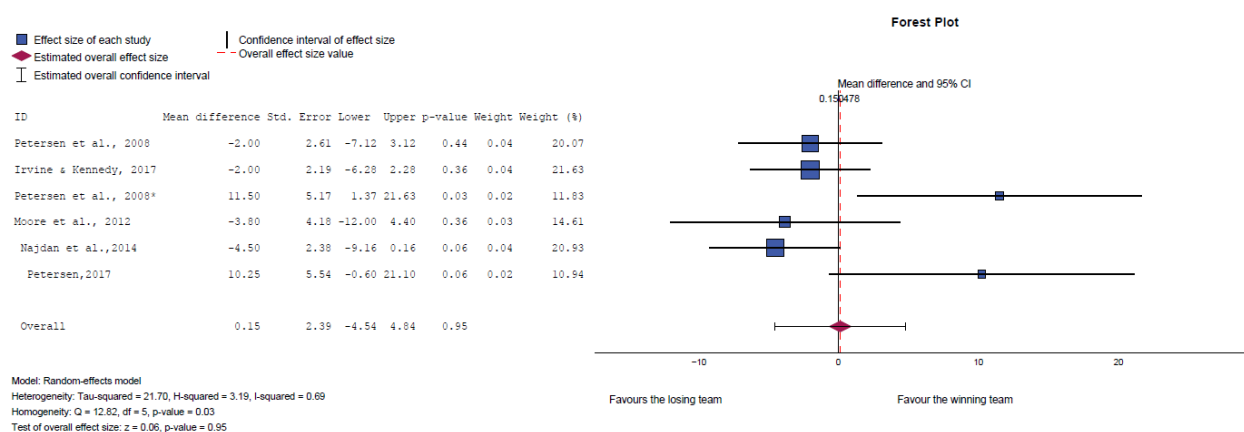


Figure 7. Forest plot of singles scored by the winning teams [10,22,29,32,43,44].

Figure 8 shows the pooled analysis for 25-run partnerships by the winning teams. There was no statistically significant difference in the number of 25-run partnerships between winning and losing teams, with a mean difference of -0.26 partnerships (95% CI: -0.75 to 0.22; $p = 0.29$). Heterogeneity was high ($I^2 = 75\%$; Q -test $p = 0.29$), suggesting variability in effect sizes between studies.

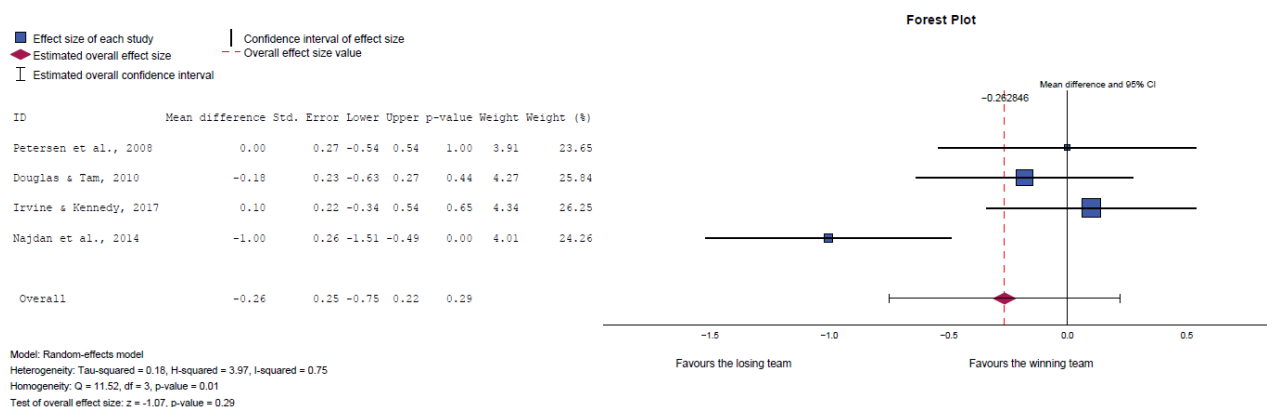


Figure 8. Forest plot of 25-run partnerships scored by the winning teams [9,10,32,43].

3.8. Bowling Performance Indicators

In Figure 9, the pooled analysis indicated that winning teams took 1.64 more wickets than losing teams, but the results were not significant (95% CI: -0.73 to 4.01 ; $p = 0.18$). Heterogeneity was extremely high ($I^2 = 98\%$; Q-test $p = 0.18$).

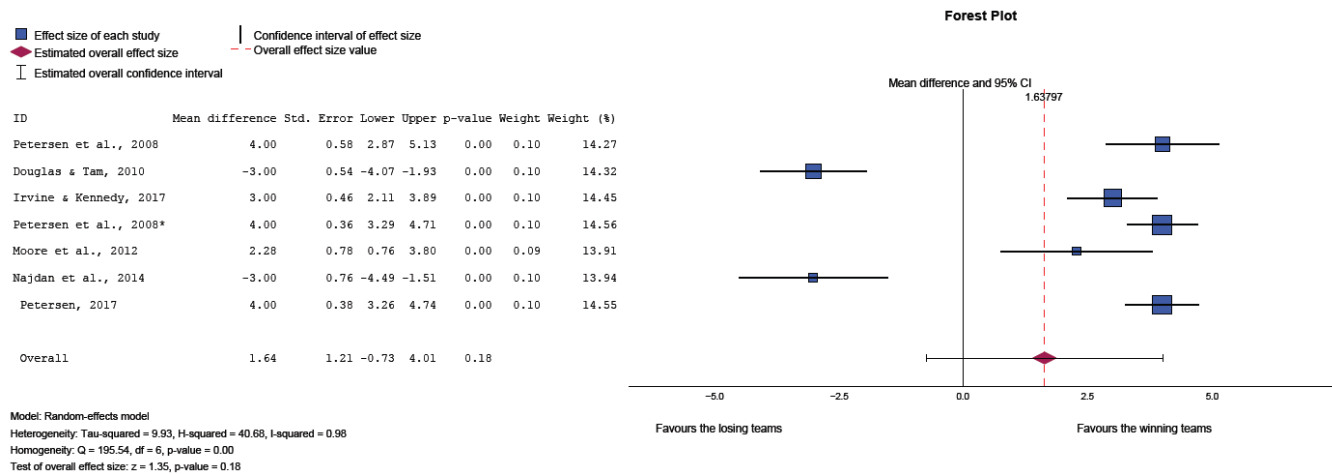


Figure 9. Forest plot of wickets taken by the winning teams [9,10,22,29,32,43,44].

In Figure 10, there was no significant difference in the number of spin balls bowled by winning and losing teams, with a mean difference of -0.62 (95% CI: -1.49 to 0.26 ; $p = 0.17$), indicating that, on average, losing teams recorded slightly higher values for spin balls than winning teams, but the differences were small and non-significant. Heterogeneity was negligible ($I^2 = 0\%$; Q-test $p = 0.92$).

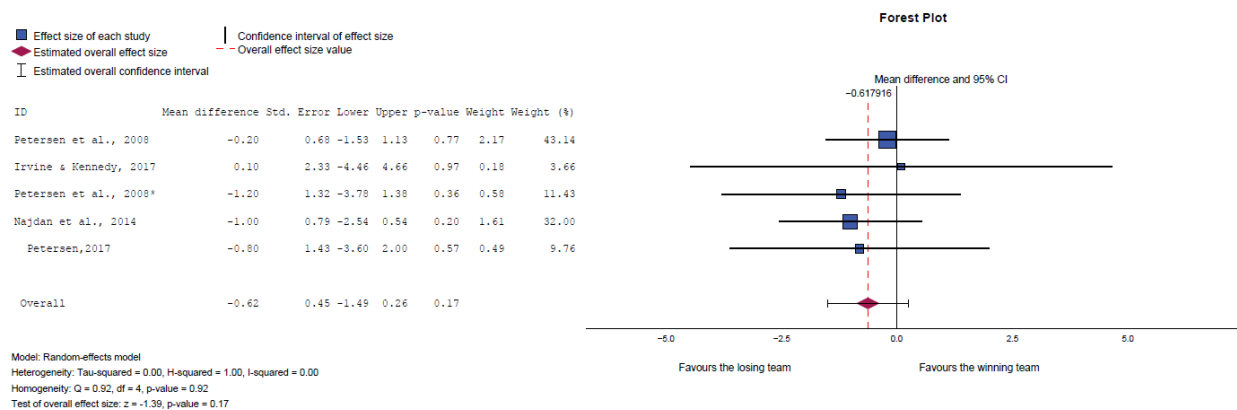


Figure 10. Forest plot of spin balls bowled by the winning teams [10,22,32,43,44].

In Figure 11, no statistically significant difference was found in the number of maiden overs bowled by winning and losing teams, with a mean difference of 0.59 overs (95% CI: -0.35 to 1.52 ; $p = 0.22$). The positive mean difference suggests that winning teams bowled maiden overs more often, but the effect was inconsistent across studies. One study [22] found a notably significant difference of $+2.08$ maiden overs in favour of winning teams. Heterogeneity was extremely high ($I^2 = 98\%$; Q-test $p = 0.22$), indicating large variation in findings across studies.

In Figure 12, the pooled analysis shows no significant difference in the number of wides bowled between winning and losing teams, with a mean difference of -0.12 wides (95% CI: -0.80 to 0.56 ; $p = 0.73$). This indicates that winning teams bowled slightly fewer wides, but the effect size was very small and not statistically significant. Petersen et al. [32] reported -0.50 wides (non-significant), while Douglas and Tam [9] and Moore et al. [29]

found a small positive difference that was also non-significant. No heterogeneity was detected ($I^2 = 0\%$; Q-test $p = 0.90$), suggesting that this minimal difference is consistent across datasets.

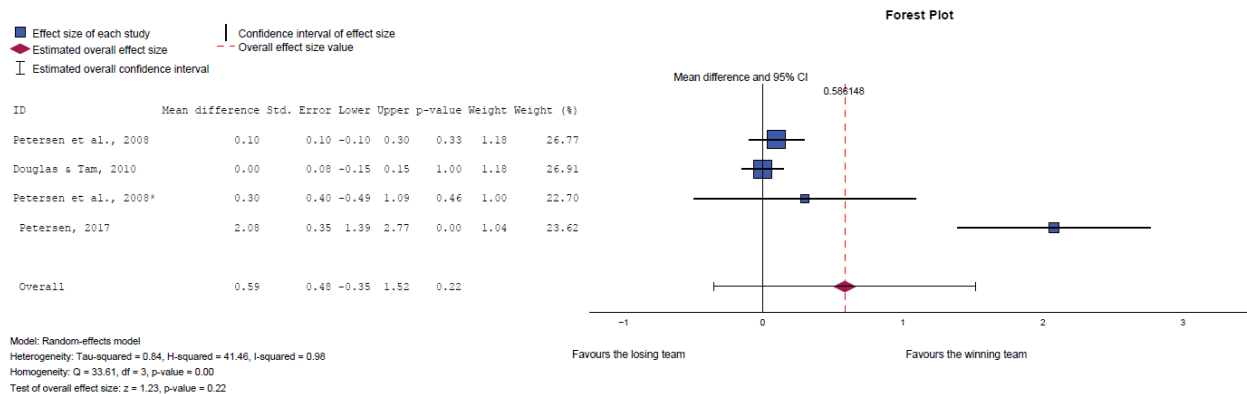


Figure 11. Forest plot of maiden overs bowled by the winning teams [9,22,32,44].

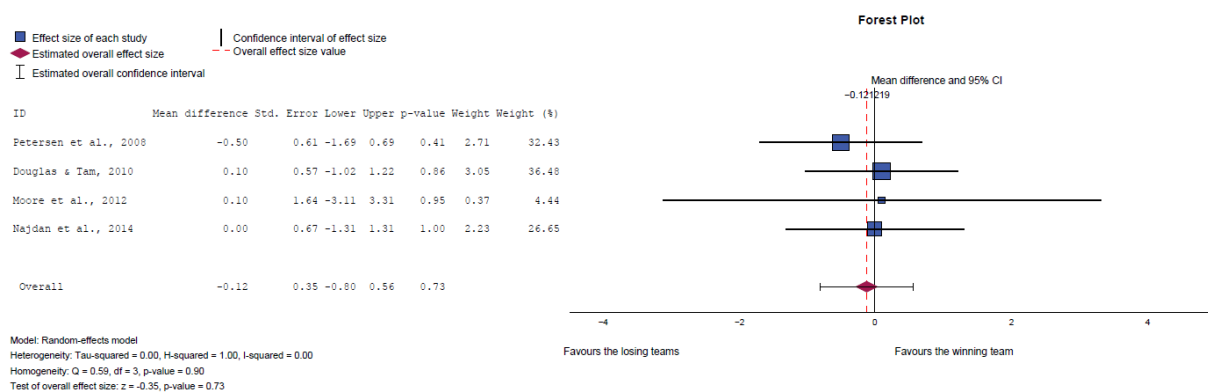


Figure 12. Forest plot of wides bowled by the winning teams [9,29,32,43].

Figure 13 shows that the winning team bowled significantly fewer no-balls than the losing teams, with a mean difference of -0.29 no-balls (95% CI: -0.56 to -0.01 ; $p = 0.04$). This finding, though small in absolute terms, suggested that bowling discipline, specifically avoiding overstepping the crease, may be associated with match success. Across studies, the direction of effect consistently favoured winning teams. Najdan et al. [44] reported -0.50 no-ball, while Moore et al. [29] and Douglas and Tam [9] observed a smaller, but similarly negative difference. Only Petersen et al. [32] reported no mean difference (0.00) in no balls. No heterogeneity was detected ($I^2 = 0\%$; Q-test $p = 0.61$), indicating that the effect size was consistent across datasets.

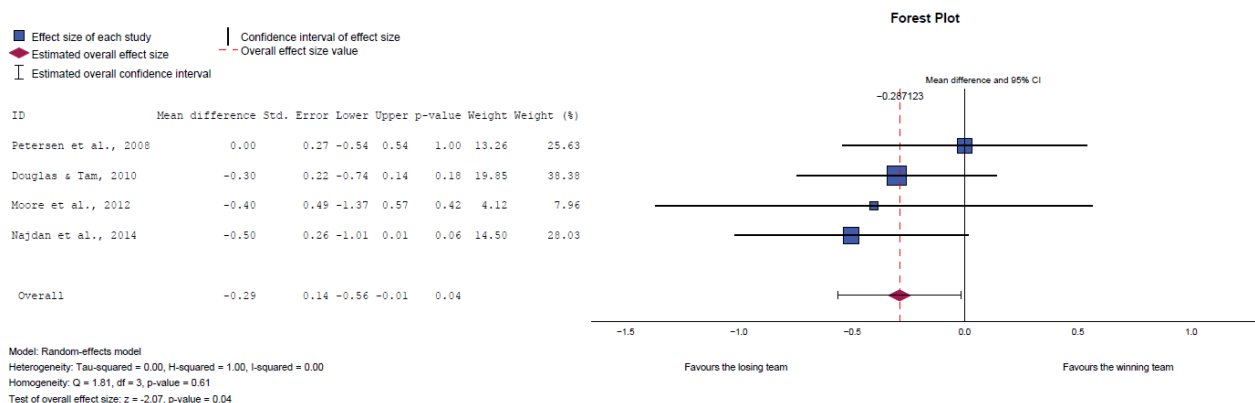


Figure 13. Forest plot of no balls bowled by the winning teams [9,29,32,43].

4. Discussion

It is noteworthy that only 29 variables were found to be associated with successful performance in the reviewed studies. In international ODIs, six variables were identified as discriminating factors between winning and losing teams, such as higher run rates, boundaries in fours, number of 50+ partnerships, taking more wickets in an innings, taking more wickets in the last six overs, and maiden overs bowled [22,45]. Across formats, the meta-analysis highlighted batting KPIs such as run rate, total runs scored and boundary frequency as the most consistent discriminators between winning and losing teams, with effects often exceeding match-defining margins (e.g., ~1.43 more runs/over or ~3–4 more sixes for winning teams). Bowling KPIs showed a more variable result, wherein teams tended to take more wickets overall, and the timing of wickets (e.g., early breakthroughs vs death overs) varied substantially between contexts. Importantly, single-scoring rates and smaller partnerships were not consistently linked to successful match outcomes, suggesting that boundary hitting and high run rates were more decisive in the modern limited-overs game. These patterns were consistent across international and domestic competitions, though ODI matches tended to favour sustained partnerships, while T20 success was more closely associated with explosive scoring in key phases of the match. Across the pooled analyses, heterogeneity ranged from moderate to very high ($I^2 = 60\text{--}98\%$), indicating that the strength and direction of KPI effects varied substantially between studies. Such variability likely reflects differences in tournament format, competition level, playing conditions and phase of the matches. This context dependency emphasises the need for performance models that integrate situational and environmental factors, rather than relying solely on aggregated KPI values. These findings reinforced the ecological dynamics view that successful performance in cricket is shaped by exploiting scoring affordance under situational constraints. In high-tempo formats like T20, exploiting high-value scoring opportunities (such as boundaries and strike acceleration) may be a more robust route to success than the incremental accumulation of runs through scoring singles. Conversely, in ODI cricket, where match tempo varies in the 50 overs, the interaction between run rate and partnership-building appears more critical, supporting tactical periodisation models that emphasise phase-specific strategy. Performance analysis in cricket plays a pivotal role in unravelling the intricacies of the game and assessing individual players' contributions [47]. The results of the present review indicated that understanding individual player performances necessitates considering the players' roles and the team's strategies [39,40,47]. Each player has specific responsibilities that influence KPIs relevant to them [48]. Neglecting these dynamics can lead to an incomplete understanding of KPIs and the contributions they make to a team's success [39]. Performance analysis becomes even more critical when individual players' performances are benchmarked against their peers or team averages [49]. Comparing a player's performance to the average or other top performers during the same period offers insights into the player's relative strengths and weaknesses. Without such comparisons, gauging the significance of a player's performance becomes challenging and speculative [3].

Although performance analysis is a growing field, the research investigating performance analysis in cricket is limited to only nine (9) relevant studies identified from the systematic review. Even though these studies provide insights into effective strategies and tactics for winning in limited-overs matches, the statistical techniques employed were limited and not fully informative in performance analysis [47]. The KPIs identified in these studies were for the shorter formats of the game (ODI and T20 cricket) and specifically for batting, bowling and fielding. However, these KPIs did not consider the opposition nor the inherent unpredictability and uniqueness of each match [48]. For instance, game behaviours often exhibit inconsistency, and performance indicators are likely to be influ-

enced by interactions between players and opponents [39]. Therefore, it is improbable that a complex and dynamic game like cricket can be adequately represented solely by isolated performance measures [47]. Another common limitation was the disproportionate emphasis on batting and bowling, while under-emphasising fielding [46]. Fielding is a pivotal facet of cricket, and solely assessing players based on their batting and bowling prowess presents an incomplete analysis [48]. Incorporating fielding metrics, such as catches taken, run-outs executed and fielding efficiency, can offer a holistic analysis [21]. In addition, some articles employed inappropriate or flawed methods, such as traditional approaches, suggesting the need for more robust and reliable analytical approaches [31]. Furthermore, some studies did not clearly explain the methodology used, making it difficult to replicate and critically evaluate [31].

Many of the studies relied heavily on conventional statistics, like batting and bowling averages, and strike rates [22,48], which limited their application in identifying and prioritising KPIs. Incorporating advanced metrics that delve into key performance aspects, such as a player's ability to score under pressure, the player's impact on match outcomes, and their effectiveness in diverse game situations, can provide a more comprehensive evaluation [21]. While these metrics offer valuable insights, they also fall short of capturing the full spectrum of a player's performance [50]. When selecting performance indicators, challenges may arise due to a lack of clarity, particularly in terms of undefined or subjective criteria [51]. This lack of clarity can hinder the comparison or replication of studies, making it challenging to advance the field of research and for coaching staff to implement proven successful practices [5,52,53].

To grasp the true essence of performance analysis, it is essential to consider the contextual factors, such as pitch conditions, weather conditions, strengths of the opposition and the match-specific conditions [47]. In the current review, only two studies incorporated contextual elements, both focusing on pitch map analysis to examine bowling strategies and delivery placement in relation to match outcomes [29,44]. Neglecting these contextual factors, such as pre-match conditions and covariates, can render the analysis incomplete or even misleading [54].

4.1. Strengths and Limitations of This Study

The review provided valuable insights into the general and specific performance indicators in professional cricket, such as batting, bowling and fielding. While the review offered critical insight into cricket performance analysis, some limitations exist. Firstly, the small number of included studies ($n = 9$) limited the synthesis of evidence in the review and may not fully represent the range of KPIs used across different formats of limited-overs cricket. In addition, most of the studies focused exclusively on male players, which decreases the generalizability of findings to female cricket and may perpetuate gender-related blind spots in performance research. Secondly, the exclusion of non-English publications may have introduced language bias, potentially omitting relevant data from regions where cricket is popular but underrepresented in English-language journals. Moreover, publication bias may not be ruled out, as studies reporting null or negative findings may be less likely to appear in peer-reviewed literature, skewing the evidence base toward positive or statistically significant KPIs. Lastly, the generalizability of findings is limited by the heterogeneity of study designs, data collection methods and contextual factors (playing conditions and match context). As such, caution should be exercised when interpreting these results in different cricketing environments, especially at the grassroots or youth level. Future studies should focus on these gaps by including more diverse populations, broader language inclusion and publication sources beyond traditional academic databases.

4.2. Practical Applications

Coaches can use these KPIs to tailor role clarity within batting orders, by assigning specific functions to players such as boundary accelerators tasked with maximizing scoring during the final overs, or wicket preservation specialists responsible for maintaining stability during the early phases of the innings. For bowlers, performance analysis should focus on phase-specific wicket-taking strategy; i.e., adopting aggressive opening spells aimed to disrupting the opposition's scoring momentum, or employing defensive containment combined with sustained wicket-taking pressure in the closing overs. Importantly, the lack of difference in scoring singles suggested that training time may be better spent on developing power-hitting and strike rate maintenance under pressure for achieving successful match performance.

5. Conclusions

The systematic review identified KPIs related to success in international ODI and T20 cricket matches, drawing from a limited but focused set of studies. The findings highlighted specific batting, bowling and fielding indicators that can influence both tactical decisions by coaches and overall match outcomes. However, the current evidence from the review remains narrow in scope, with limited attention to contextual factors and a significant underrepresentation of female cricketers. To strengthen the scientific and practical impact of KPI research in cricket, future studies should move beyond static models to more contextual and individualised KPI models. Additionally, AI-driven analytics and dynamics modelling could integrate match conditions, opposition profiles and live performance feeds to generate real-time tactical recommendations. Also, player-specific KPI dashboards could track individual contributions relative to role expectations, enabling targeted skill development. These approaches would help bridge the gap between research theory (findings) and practice (in-game decision-making). Additionally, incorporating gender-specific analyses to ensure inclusivity and broader applicability may help in integrating contextual match variables in order to improve KPI interpretation that could assist coaches and sport analysts in appreciating the value of role-specific and phase-specific KPIs, the importance of translating data into actionable insights during match preparation and in game decisions; advance analytics tools, including machine learning and dynamic modelling, to extract predictive KPIs and support real-time decision-making; and mixed-methods approaches that incorporate coaches' perspectives to bridge the gap between quantitative findings and practical application. Most research adopts a purely quantitative approach, with limited integration of how coaches interpret and apply KPI data in elite environments, a gap that constrains the translation of research into practice.

6. Patent

Protocol Registration

Details of the protocol for this systematic review were registered on Open Science Framework (protocol reference: 10.17605/OSF.IO/HGE4J).

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/app151910341/s1>. Supplementary S1: Search strategy for databases; Supplementary S2: Eligibility screening form; Supplementary S3: Data extraction form; Supplementary S4: PRISMA_2020_checklist.

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L.L.L., M.S.T., H.C. and C.N.; project administration, R.V.N.; funding acquisition, R.V.N. All authors have read and agreed to the published version of the manuscript.

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