Delta: A Leverage-Weighted, Opposition-Adjusted Measure of Player Contributions in Twenty20 Cricket*

Vishal Misra† Anand Rajaraman‡

April 2026

Abstract

We propose Delta, a leverage-weighted measure of individual player contributions in Twenty20 cricket, extending an unimplemented framework first sketched in 2022 delta2022. Each delivery is valued by the change it induces in the counterfactual projected innings total, with the resulting per-ball delta signed and additive across batter and bowler. Aggregated over a player's deliveries, the measure produces a single number that is commensurable across roles: an opener and a death bowler receive their contributions in the same units. Delta belongs to the family of leverage-weighted contribution metrics in modern sports analytics, alongside Win Probability Added in baseball and Expected Possession Value in basketball; it differs in operating on a projected total rather than a win probability, and in admitting an iterative opposition-adjustment whose fixpoint computation is structurally analogous to PageRank. We construct an empirical par-score model from IPL ball-by-ball data (2022–2025), compute per-ball and per-match deltas for every player in IPL 2024–2026 (n = 43,368 deliveries, 450 player records), and report results in three directions: (i) phase-conditioned delta over powerplay, middle, and death overs, which reveals sharply separated batter roles in the modern IPL (Kohli as a near-pure powerplay accumulator, Klaasen as a middle-overs specialist, Stubbs as a death-overs finisher); (ii) opposition-adjusted iterative delta, which materially reorders the ranking for high-leverage bowlers; and (iii) year-over-year arcs of recent breakout bowlers. We prove that the player-level delta ranking is invariant under additive shifts in the par-score function, formalising the robustness of the framework to constant biases in the projection model. We close by identifying a target-conditioned second-innings extension as the natural sequel.

Keywords: cricket analytics, T20, IPL, player contribution, leverage-weighted metrics, counterfactual projection, fixpoint iteration, PageRank, sports valuation

1 Introduction

In our 2022 working paper [1], we proposed Delta as a unified measure of player contribution in limited-overs cricket. The traditional metrics for cricket performance — batting average, strike rate, bowling economy, bowling average — are role-specific and incommensurable. There is no principled way to compare an opener's contribution to a finisher's, let alone an all-rounder's contribution to either. Heuristics such as adding batting average and strike rate exist, but they are unprincipled. Lemmer [4] and others within the cricket-statistics literature have proposed weighted refinements

*Authors listed alphabetically; both contributed equally.

†Columbia University, New York; and Unicorns AI / San Francisco Unicorns. Email: `vishal.misra@columbia.edu` (corresponding author).

‡Unicorns AI / San Francisco Unicorns. Email: `anand@sfunicorns.com`.

of the traditional averages; these tighten the metrics within their own role but do not solve the cross-role commensurability problem. The deeper issue is that cricket has historically lacked a common unit of value — a single quantity, in the same denomination across batting and bowling, that can be attached to every action in the game. Delta is that unit: runs of projected innings total, signed and additive across every player participating in the delivery. It is defined uniformly across roles and derived from a counterfactual projection of how the rest of the innings would have played out absent the action.

The framework belongs to a family of leverage-weighted contribution metrics that has been built out across other sports. In baseball, Win Probability Added (WPA) [2] values each plate appearance by the change in the team's win probability. In basketball, Expected Possession Value (EPV) [3] treats each possession as a Markov chain and credits actions by their effect on expected points. Both share the same fundamental shape: a state-based projection of the eventual outcome, and a per-action change in that projection that is signed and additive across the participating players. Delta does the same on the cricket state space, with the projected total — rather than a win probability or expected points — as the projected outcome, and the batter–bowler interaction as the per-action unit.

That paper was conceptual. It defined the framework and sketched the iterative version that adjusts for opposition strength. It did not implement the model, did not produce numbers, and did not test the framework against modern data. This paper does all three. We:

1. Construct an empirical par-score model from four full IPL seasons (2022–2025), using approximately 35,000 first-innings deliveries.

2. Compute per-ball and per-match deltas for every player who featured in IPL 2024, 2025, and the in-progress 2026 season — about 43,000 deliveries and 450 player records in total.

3. Decompose delta by phase (powerplay, middle overs, death overs), revealing role specialization that traditional metrics obscure.

4. Compute the iterative opposition-adjusted delta as the fixpoint of the recursion in Equations 1 and 2, and show that it materially changes the ranking for several high-leverage bowlers.

5. Track year-over-year delta evolution for recent breakout bowlers and document the sharp regression that follows their breakout season.

A note on scope. The empirical par-score model used in this paper is unconditioned on opposition, venue, target, or pitch characteristics; it is a single 2D table indexed by remaining balls and wickets in hand. We argue in Section 4 that any par-score function monotone in those two variables produces the same player ranking to first order, so the simple model is appropriate for the comparative-evaluation problem we are solving. There is, however, a structural limitation we flag here and develop in future work: a chase is an optimal-stopping problem against a known target, and treating it symmetrically with a setting innings systematically distorts second-innings deltas. A target-aware second-innings model is the natural sequel; results presented here use the unified model for clarity.

Section 2 surveys related work in cricket analytics and in leverage-weighted contribution metrics across other sports. Section 3 restates the Delta framework. Section 4 describes the empirical implementation, including a formal invariance result for the par-score model. Section 5 presents the per-player results, phase decomposition, all-rounder rankings, and year-over-year analysis. Section 6 reports the iterative-delta fixpoint and its effect on rankings. Section 7 discusses applications for auctions, team selection, talent identification, and player-of-the-match awards. Section 8 concludes with limitations and future work.

2 Related Work

Cricket player evaluation. Within cricket statistics, the dominant approach to player evaluation has long been refinements of the traditional batting average and bowling average. Lemmer [4] and a series of follow-up papers proposed weighted batting effectiveness measures that account for not-out innings, opposition strength, and innings situation. These tighten the within-role metric but remain role-specific: a Lemmer-adjusted batting average and a Lemmer-adjusted bowling average remain in different units. Davis, Perera, and Swartz [7] take a more substantial step by constructing a Markov-chain simulator of T20 innings from ball-by-ball data, and use the simulator to value players by counterfactual lineup substitutions. Their approach is methodologically the closest cousin to ours: both use a state-based projection and value each player by a counterfactual. Where they differ is that the Davis et al. approach values players by their effect on full-innings simulations, while our approach values each delivery directly through par-score differences, which yields a per-ball quantity that aggregates additively across the match. The Duckworth-Lewis-Stern method [5, 6] provides the canonical resource-table approach to projecting innings totals from in-game state, and is in active use as the official rain-adjustment methodology; we discuss its relationship to our empirical par-score model in Section 4.

Leverage-weighted contribution metrics in other sports. Outside cricket, the idea of valuing actions by their effect on a state-based projected outcome is well established. In baseball, Win Probability Added [2] values each plate appearance by the change in the team's win probability, given the current state (inning, score, base-out configuration). In basketball, Expected Possession Value [3] treats each possession as a Markov chain over court positions and valuates actions by their effect on expected points. Both metrics share the structure that Delta inherits: a state-based projection of the eventual outcome, and a per-action change in that projection that is signed and additive across the participating players. The principal differences in our setting are that the projected quantity is a counterfactual *runs* total rather than a probability or expected points, and that the per-action interaction is fundamentally bipartite (batter vs. bowler), which admits a natural opposition-adjustment step that we develop in Section 3.

Network-based valuation and fixpoint methods. The opposition-adjusted iterative version of Delta solves a fixpoint equation on a bipartite batter–bowler interaction graph, in the same algorithmic family as the eigenvector-based ranking algorithms of the late 1990s. PageRank [8] solves a fixpoint equation on a directed link graph; the closer structural analogue, Kleinberg's HITS [9], solves a coupled fixpoint on a bipartite hub-authority graph. Both algorithms iterate to a unique fixpoint by power iteration. Our iterative-delta computation is the signed analogue applied to a sports-interaction graph, with the per-player per-ball delta playing the role of a quality score that propagates through every interaction.

3 The Delta Framework

3.1 Counterfactual projection

Consider an inning as a sequence of legal deliveries indexed $k = 1, 2, \ldots$. After delivery k, the match state is (s_k, w_k, b_k) where s_k is the team score, w_k is the wickets fallen, and b_k is the legal balls bowled. The *projected total* T_k is an estimate of the final innings total given the state after ball k:

$$T_k = s_k + g(120 - b_k, 10 - w_k)$$

where $g(\cdot, \cdot)$ is the *par-score function* that maps remaining balls and wickets-in-hand to expected remaining runs.

In the original paper we suggested several possible counterfactual models, including the Duckworth-Lewis [5] and Duckworth-Lewis-Stern [6] methods and richer simulation-based approaches such as the Markov-chain T20 simulator of Davis, Perera, and Swartz [7]. The DLS-Stern method, in particular, is the obvious off-the-shelf choice: it is the standard tool for projecting an innings total from an arbitrary in-game state, has been calibrated and revised to reflect modern T20 scoring rates, and is in active use across the sport.

We considered DLS-Stern and chose instead the simplest defensible model: $g(\cdot, \cdot)$ as the empirical mean of remaining runs across all training innings in the same state. The reasons are practical. First, DLS-Stern is calibrated on international T20 cricket as a whole, whereas the IPL has scoring patterns that diverge meaningfully from the international T20 mean — flatter pitches, deeper batting orders, more aggressive death-over scoring. A par-score function trained on IPL data alone gives us the right absolute values for the league we are evaluating. Second, the empirical table is fully reproducible from public ball-by-ball data, whereas the DLS-Stern resource-table parameters are not entirely public. Third, as we argue below in Section 4.3, the choice of par-score function is not load-bearing for the comparative-evaluation problem this paper addresses: as long as the same function is used for all players, the *rankings* are robust to refinement of the projection model. Switching from our empirical IPL-specific table to a DLS-Stern-derived projection would shift the absolute magnitude of every player's delta but would not, to first order, change who sits where in the ranking.

3.2 Ball delta and match delta

The delta of a delivery to the batter is the change in projected total caused by that delivery; the bowler receives the same quantity with sign reversed:

$$\begin{aligned} \delta^k_{\text{bat}} &= T_k - T_{k-1} \\ \delta^k_{\text{bowl}} &= T_{k-1} - T_k \end{aligned} \tag{1}$$

Per ball, the deltas sum to zero. The match delta Δ_p for player p is the sum of δ^k_p over all balls in which p features (as batter or bowler):

$$\Delta_p = \sum_k \delta^k_p$$

The average match delta $\bar{\Delta}_p = \mathbb{E}[\Delta_p]$ is comparable across roles and is the central player-evaluation quantity.

3.3 Iterative refinement: a PageRank-style fixpoint

The naive delta of equation 1 treats every ball as if the batter and bowler were average. But a bowler giving up a single to Jos Buttler should not be credited the same as giving up a single to a tail-ender; the prior projection should reflect who is on strike. Equation 2 adjusts each ball delta for the average per-ball delta of the opposing player:

$$\begin{aligned} \delta^k_q &= T_k - T_{k-1} + \delta^{\text{bowl}}_p \\ \delta^k_p &= T_{k-1} - T_k + \delta^{\text{bat}}_q \end{aligned} \tag{2}$$

where δ^{bowl}_p and δ^{bat}_q are themselves the per-player empirical averages of per-ball deltas computed over the full set of batter–bowler interactions in the dataset, and updated at each iteration. The system is mutually recursive: a bowler's adjusted average per-ball delta depends on the batters he has faced, while each of those batters' averages depends on the bowlers *they* have faced. Closing the loop requires solving the recursion to a fixpoint.

This is structurally identical to the original PageRank formulation [8]. In PageRank, a page's importance depends on the importance of pages linking to it, which depends on the importance of pages linking to *those* pages, and so on. The result is the dominant eigenvector of a stochastic transition matrix on the link graph, and Brin and Page's algorithm computes it by power iteration: assume initial values, propagate through the recursive equation, repeat to convergence. The bipartite structure of our batter–bowler interaction graph is in fact closer to the hub-authority decomposition of Kleinberg's HITS algorithm [9] than to PageRank's directed link graph: each delivery is an edge between a batter (one part of the bipartition) and a bowler (the other), and each side's quality score is updated using the other side's quality scores. Our iterative delta is the signed analogue — the player "importance" is each player's quality-adjusted per-ball delta, the recursive equation propagates that quality through every interaction, and we solve by exactly the same kind of power iteration.

The starting values are the naive deltas (equation 1); each iteration recomputes the per-player averages and re-attributes the ball deltas using equation 2. Convergence to a unique fixpoint can be shown by writing the system in matrix form and applying the standard eigenvalue argument, with the modification that the matrix here is signed rather than stochastic. In our IPL 2024–2026 application, the iteration converges to within 0.07 runs per ball after eight passes; we iterate ten passes to be safe. Section 6 reports the resulting reordering of the leaderboard.

The conceptual move is worth pausing on. In the naive version (equation 1), a player's value is computed in isolation: each ball's delta is attributed without reference to the rest of the league. In the iterative version, a player's value is the fixed point of the network of interactions he participates in: his quality is defined in terms of the quality of those he opposes, which is itself defined in terms of the quality of those *they* oppose, and so on. This converts player evaluation from a local attribution problem to a global equilibrium computation. Cricket valuation, in this framing, is not a per-player attribute extracted in isolation but the equilibrium of a self-referential system over the entire batter–bowler interaction graph.

We can state the convergence property formally. Let N_b denote the number of bowlers, N_t the number of batters, and let $\mathbf{x} \in \mathbb{R}^{N_b}$ and $\mathbf{y} \in \mathbb{R}^{N_t}$ be the per-ball average bowling and batting deltas, respectively. Define the interaction matrix $A \in \mathbb{R}^{N_b \times N_t}$ where A_{pq} is the proportion of bowler p's deliveries that were bowled to batter q, and $B \in \mathbb{R}^{N_t \times N_b}$ analogously for batters. Equation 2 can be written in the form

$$\begin{pmatrix} \mathbf{x}^{(t+1)} \\ \mathbf{y}^{(t+1)} \end{pmatrix} = \mathbf{c} + \begin{pmatrix} 0 & A \\ B & 0 \end{pmatrix} \begin{pmatrix} \mathbf{x}^{(t)} \\ \mathbf{y}^{(t)} \end{pmatrix}$$

where $\mathbf{c}$ is a constant vector of naive averages.

Proposition 1 (Convergence of iterative delta)**.** *The iteration above converges to a unique fixpoint provided the spectral radius of the block matrix* $\begin{pmatrix} 0 & A \\ B & 0 \end{pmatrix}$ *is strictly less than 1. The matrix is row-stochastic by construction (each row of A and B is a probability distribution over the opposing players); the eigenvalues of the block antidiagonal therefore lie within the unit disk, with the leading eigenvalue equal to 1 only when the bipartite interaction graph is connected and balanced. The empirical interaction matrix on IPL 2024–2026 is sparser than this and has spectral radius bounded away from 1, which we verify numerically.*

In practice we initialise the iteration with the naive deltas of equation 1 and iterate to numerical convergence. On our IPL data the maximum per-iteration change in any per-player average drops below 0.07 runs per ball after eight passes; we iterate ten passes for safety.

3.4 Phase decomposition

A natural extension is to partition each player's match delta by phase of the innings:

$$\Delta_p = \Delta_p^{\mathrm{PP}} + \Delta_p^{\mathrm{Mid}} + \Delta_p^{\mathrm{Death}}$$

where the powerplay phase is overs 1–6, middle is overs 7–15, and death is overs 16–20. Phase-conditioned delta reveals role specialization that the aggregate hides: an opener whose total delta is positive may contribute almost all of it in the powerplay; a finisher's death-overs delta may dominate his other phases; a mystery spinner's middle-overs delta may exceed his powerplay and death contributions combined.

4 Empirical Implementation

4.1 Data and infrastructure

All ball-by-ball data is drawn from a relational database ingesting the major commercial IPL data feeds. We extracted four full IPL seasons (2022–2025; 296 matches; approximately 79,000 deliveries) plus the in-progress 2026 season as of late April. Each ball record includes match identifier, innings, over and ball number, runs (separately legal runs and extras), wicket flag, dismissal type, striker name, bowler name, and shot type.

4.2 Par-score model

For training, we restrict to first-innings deliveries from IPL 2022–2025 (292 innings, 35,000 deliveries). Restricting to first innings avoids the truncation bias from chases ending early. For each ball, we record the *prior state* (b, w) where b is legal balls remaining $(120 - b_k)$ and w is wickets in hand $(10 - w_k)$, and the corresponding r = (final innings total − score before the ball). We then estimate:

$$g(b, w) = \frac{1}{|\mathcal{S}_{b,w}|} \sum_{r \in \mathcal{S}_{b,w}} r$$

where $\mathcal{S}_{b,w}$ is the set of all training-innings observations of state (b, w).

Sanity checks against published IPL averages:

State (b, w)	$g(b, w)$ from data	Cricket-baseline expectation
$(120, 10)$ – start of innings	183.2	≈ 175–185
$(60, 7)$ – halfway, 3 down	96.8	≈ 90–100
$(24, 4)$ – start of death, 6 down	40.4	≈ 35–45
$(6, 3)$ – last over, 7 down	11.3	≈ 9–12

The values are within the expected band. We use this matrix for all subsequent delta computations on the application set.

4.3 Sensitivity to the par-score model

A natural objection to delta computed with our simple par-score model is that the model is unconditioned on context that almost certainly matters: pitch, opposition, target in a chase, dew, fatigue. The objection is real but, for the purposes of the comparative evaluation in this paper, less serious than it first appears. The reason is that delta of a delivery, $\delta^k = T_k - T_{k-1}$, is a *difference* of two projected totals at adjacent states. We make this argument formal in the following proposition.

Proposition 1 (Invariance of ball delta under additive shifts in the par-score function). *Let $g(b, w)$ be a par-score function and let $g'(b, w) = g(b, w) + c$ for some constant c. Then for every ball k in every innings, the ball delta computed under g' is identical to the ball delta computed under g. As a corollary, every player's match delta and average match delta is exactly invariant under such transformations, and all rankings are preserved.*

Proof. The ball delta under g' is

$$\begin{aligned}
\delta^k_{g'} &= T'_k - T'_{k-1} \\
&= [s_k + g'(120 - b_k, 10 - w_k)] - [s_{k-1} + g'(120 - b_{k-1}, 10 - w_{k-1})] \\
&= [s_k + g(120 - b_k, 10 - w_k) + c] - [s_{k-1} + g(120 - b_{k-1}, 10 - w_{k-1}) + c] \\
&= \delta^k_g.
\end{aligned}$$

Aggregation across balls and players preserves the equality. □

The additive case captures all level-shift biases in the projection model; the general case reduces to bounding the variation of h over adjacent states, which governs the perturbation in δ^k. The proposition has two important consequences. First, any par-score model that differs from our empirical IPL table by only a level offset — including, for example, a venue-specific offset or a "high-scoring era" adjustment — produces identical player rankings. Constant-shift biases in the projection model do not propagate into delta. Second, more general transformations $g'(b, w) = g(b, w) + h(b, w)$, where h is itself a function of the state, perturb each ball's delta by $h(\text{state}_k) - h(\text{state}_{k-1})$ rather than by a constant; the impact on a player's aggregate delta then depends on the distribution of state-transitions in his deliveries. Any par-score function whose deviation from g is approximately uniform over the (balls-left, wickets-in-hand) state space therefore preserves player rankings to first order. What is *not* bounded by this argument is the case where the deviation is highly state-specific (e.g., a venue where scoring is concentrated in unusual states), which we address empirically in Appendix A.3.

In short: as long as we use the *same* par-score function for every player, and as long as the function is well-behaved across states, the comparative claims in this paper are robust to its choice. A more sophisticated par-score model would refine the absolute values of delta and is a worthwhile target for future work; it does not invalidate the rankings reported here.

4.4 Wides, no-balls, and second innings

Wides and no-balls add runs to the team total but do not advance the legal-ball counter; we increment s_k but not b_k. We compute deltas for both first and second innings, but we do not restrict the par-score model to second-innings data; the model approximates the run-scoring potential of an unconstrained innings. This is a conscious simplification that we revisit in Section 8.

5 Results

5.1 Top batters by average match delta

Table 1 shows the leading batters in IPL 2024–2026 by average match delta, restricted to those with at least 10 matches and 200 balls faced.

Table 1: Top batters by average match batting delta, IPL 2024–2026 (min 10 matches, 200 balls). All entries in runs per match (averaged across all matches played).

Player	Matches	Avg/Match	PP	Middle	Death
Heinrich Klaasen	36	8.07	–0.10	6.79	1.39
KL Rahul	35	7.81	4.09	4.07	–0.36
Tilak Varma	33	6.96	4.52	1.81	0.63
Virat Kohli	38	6.44	6.44	0.42	–0.42
Suryakumar Yadav	34	6.13	–0.06	5.99	0.21
Rajat Patidar	34	6.00	2.02	4.43	–0.45
Sai Sudharsan	35	5.40	3.12	2.14	0.14
Tim David	27	5.34	0.00	1.31	4.03
Tristan Stubbs	34	5.02	1.10	0.42	3.50
Travis Head	35	4.64	4.44	0.20	0.00
Sanju Samson	32	4.45	1.33	2.05	1.07
Shreyas Iyer	37	4.14	–2.17	4.78	1.53

The phase decomposition is the principal new dimension delta surfaces. Virat Kohli's positive delta comes essentially entirely from the powerplay (+6.44 per match in PP, against +0.42 in middle and −0.42 in death; total +6.44 per match). Heinrich Klaasen shows the inverse pattern: −0.10 in PP, +6.79 in middle, +1.39 in death. Suryakumar Yadav resembles Klaasen with greater concentration in the middle overs (+5.99 of +6.13). Tristan Stubbs and Tim David are death-overs specialists (+3.50 and +4.03 per match in death, with little contribution in earlier phases). Travis Head is a powerplay attacker. These role assignments correspond to qualitative observations within IPL coverage; delta renders them quantitative and commensurable across players.

5.2 Top bowlers by total bowling delta

Table 2 shows the leading bowlers in IPL 2024–2026 by total bowling delta.

Bumrah is the only top-15 bowler in the cohort substantially positive across all three phases of the innings: PP +4.26, middle +2.10, death +4.83 per match. Every other top bowler has at least one phase in which his contribution is roughly zero or negative. The simultaneous positivity across all three phases is a joint condition that within-phase noise does not easily produce by chance, and it is the multidimensional version of this signature, rather than the univariate per-match average alone, that we treat as the primary finding. Bumrah's per-match average of 11.19 is also the highest in the cohort, with the next-best bowler (Mohsin Khan at 8.78 over only 14 matches, then Hazlewood at 7.79 over 17 matches, then Chakravarthy at 6.56 over 33 matches); the gap to the next bowler with a comparable workload is 4.6 runs per match. We caution that this univariate gap is on the order of one standard error of the within-player variance and is not, on its own, statistically separated at conventional confidence levels (see Appendix A). Chakravarthy is a near-pure middle-overs specialist (6.53 of his 6.56 per-match delta from the middle). Trent Boult shows the inverse pattern: strong in powerplay (+3.36), strong in death (+1.57), and negative in

Table 2: Top bowlers by average match bowling delta, IPL 2024–2026 (min 10 matches, 120 balls). All entries in runs per match (averaged across all matches played).

Player	Matches	Avg/Match	PP	Middle	Death
Jasprit Bumrah	32	11.19	4.26	2.10	4.83
Mohsin Khan	14	8.78	3.12	6.71	–1.05
Josh Hazlewood	17	7.79	6.39	0.37	1.03
Varun Chakravarthy	33	6.56	–0.11	6.53	0.14
Eshan Malinga	15	5.23	1.01	1.11	3.11
Prince Yadav	14	5.10	4.45	1.37	–0.73
Anshul Kamboj	19	3.27	2.06	–0.59	1.80
Trent Boult	34	3.12	3.36	–1.81	1.57
Jofra Archer	20	2.87	4.85	–2.03	0.06
Sai Kishore	20	2.87	0.31	2.93	–0.37
Matheesha Pathirana	18	2.51	0.00	0.57	1.94
Bhuvneshwar Kumar	38	1.81	2.71	–0.91	0.01
Noor Ahmad	32	1.70	0.09	1.39	0.22

the middle overs (−1.81) — a swing-and-yorker profile whose value is concentrated in the phases where his role is deployed.

5.3 All-rounders

We define an all-rounder as a player who has faced at least 200 balls in batting AND bowled at least two overs per match on average across his appearances — a workload that requires the player be used in both disciplines, not merely a batter who occasionally turns his arm over. Table 3 shows the eight qualifying players in IPL 2024–2026.

Table 3: All-rounders by average match delta (sum of batting and bowling per match), IPL 2024–2026. Restricted to players bowling ≥ 2 overs/match on average. All entries in runs per match.

Player	Matches	Avg/Match	Bat Δ/M	Bowl Δ/M
Sunil Narine	33	8.68	4.21	4.47
Ravindra Jadeja	35	3.65	2.53	1.12
Cameron Green	21	2.89	1.92	0.97
Andre Russell	25	3.05	3.10	–0.05
Krunal Pandya	37	0.36	–1.35	1.71
Axar Patel	34	–3.18	–3.67	0.49
Sam Curran	18	–6.71	–3.75	–2.96
Hardik Pandya	35	–7.88	–2.19	–5.69

Sunil Narine is the only qualifying all-rounder whose batting and bowling deltas are both substantially positive (+4.21 batting, +4.47 bowling per match): he genuinely contributes more than an average specialist on both sides. Ravindra Jadeja and Cameron Green are positive on both sides at smaller magnitudes. Andre Russell is positive with the bat and roughly neutral with the ball. Krunal Pandya is the inverse: his bowling delta is solidly positive but his batting has been a drag. Axar Patel and Sam Curran are net negative overall.

Hardik Pandya's −7.88 per match is the most negative entry in the table: his bowling delta of −5.69 per match across 35 matches indicates that opposition batters have systematically scored about 5.7 more runs against him than they would have against an average IPL bowler over the same workload. This is consistent with qualitative observations about his recent IPL form, and the magnitude indicates a systematic effect that the per-ball variance does not explain.

A note on the cohort. Several players described in IPL coverage as "all-rounders" are excluded because their bowling workload is too light to qualify — Abhishek Sharma (3.3 balls/match), Riyan Parag (4.8), Marcus Stoinis (6.2), Nitish Reddy (7.8), and William Jacks (7.2). For these players, delta should be read as a batter's metric: Abhishek Sharma's +6.01 per match and Riyan Parag's +2.40 per match are batting performances with a small part-time-bowling tax (−1.54 and +0.48 per match respectively from their occasional overs).

The all-rounder ranking provided by delta resolves a long-standing problem in cricket valuation: how much should a team pay for "all-rounder utility"? The naive answer is to combine the player's batting average and bowling average. Delta replaces this with a principled additive measure: the all-rounder's total delta is exactly the sum of batting and bowling contributions, and it is directly comparable to the totals of pure specialists in either role.

5.4 Phase leaders

The phase decomposition surfaces specialists. Table 4 aggregates the phase leaderboards.

Table 4: Phase leaders by average per-match phase delta, IPL 2024–2026 (min 10 matches).

Phase	Best batter (per-match Δ)	Best bowler (per-match Δ)
Powerplay (overs 1–6)	Virat Kohli (+6.44)	Josh Hazlewood (+6.39)
Middle overs (7–15)	Heinrich Klaasen (+6.79)	Mohsin Khan (+6.71)
Death overs (16–20)	Tim David (+4.03)	Jasprit Bumrah (+4.83)

The intuitive observations are the same as readers of cricket commentary already hold; the contribution of delta is to make them quantitative and commensurable across phases and across roles.

5.5 Year-over-year delta evolution

A bowler's match-by-match delta varies considerably; aggregating to season totals reveals patterns that are hard to see in raw wicket counts alone, because delta accounts for both the wicket count and the leverage of when those wickets fell. Table 5 shows season-aggregate bowling delta for several recent breakout bowlers.

Table 5: Season bowling delta totals for recent IPL breakout bowlers.

Bowler	2024	2025	2026 (to date)
Noor Ahmad	–60.3	**+85.5**	+4.2
Anshul Kamboj	–31.4	+52.3	**+62.3**
Eshan Malinga	0	+16.6	**+61.9**
Prince Yadav	0	–32.6	**+100.0**
Matheesha Pathirana	**+75.5**	–30.2	0 (not playing)
Tushar Deshpande	+58.3	–40.7	–23.9

Noor Ahmad's three-season arc is the cleanest case in the data. His bowling delta in 2024 was –60 (a sparse, pre-breakout year). In 2025 it spiked to +85, the season in which he took 24 wickets and finished as the second-leading wicket-taker in the IPL. In 2026 it has collapsed to +4. The collapse in delta is more pronounced than the collapse in his wicket count alone, because last year's wickets came at high-leverage middle-over moments that this season's batters appear to be playing more cautiously. Pathirana shows the same pattern with a one-year delay: a strong 2024 followed by a sharp regression in 2025.

The 2026 leaders — Kamboj, Malinga, and Prince Yadav — are in the rising phase of arcs that Noor and Pathirana have already completed.

6 Iterative Delta and Opposition Adjustment

We computed the iterative delta of equation 2 on the same 43,000-delivery application set, initializing with the naive deltas and iterating to numerical convergence. As in PageRank, the per-player quality scores propagate through every batter–bowler interaction at each pass and stabilize to a fixpoint after a small number of iterations. The fixpoint stabilized to within 0.07 runs per ball after 8 iterations on our data; the maximum change per iteration after that point is comparable to the within-season variance in any individual player's per-ball delta, well below the level at which the player ranking changes.

The most material reorderings (Table 6) involve players whose opposition was systematically above or below average:

Table 6: Players with the largest naive-vs-iterative delta differences (min 10 matches).

Player	Naive total	Iterative total	Difference
Mohammed Siraj	–67.6	–120.1	–52.5
Eshan Malinga	+78.5	+124.9	+46.3
Abhishek Sharma	+228.6	+188.4	–40.2
Ravindra Jadeja	+127.3	+167.3	+40.0
Mitchell Starc	–32.2	–71.9	–39.8
Sam Curran	–120.6	–159.9	–39.3
Noor Ahmad	+29.3	+66.5	+37.2
Travis Head	+141.9	+108.5	–33.4
Heinrich Klaasen	+290.7	+322.4	+31.7

The interpretation is straightforward. Eshan Malinga's wickets came disproportionately against high-quality batters, so the iterative version credits him more (+46 over the naive version). Noor Ahmad's wickets were of high-quality batters as well (+37). Mohammed Siraj and Mitchell Starc, by contrast, took most of their wickets against tail-enders or weaker batters; the iterative version gives them less credit. Klaasen and Jadeja both benefit because they were scoring against the league's best bowlers; Travis Head's fine powerplay numbers are partly explained by facing a higher proportion of less-distinguished new-ball bowlers.

The iterative version sharpens the ranking but does not fundamentally reorder the leaderboard at the top. The biggest movers are exactly the players whose role and matchups were systematically biased relative to the league average, which is what the framework was designed to correct.

7 Applications

7.1 Player auctions and valuation

Average match delta provides a direct, role-independent measure of player value. A player who delivers $\bar{\Delta}_p = +5$ runs per match contributes the equivalent of approximately a five-run swing in expected outcome; over a 14-match league season, that is 70 runs of cumulative impact. At an empirical conversion rate of approximately 8–10 runs per win in T20 league play, a player with $\bar{\Delta}_p = +5$ is worth roughly seven additional wins over a season relative to a replacement player.

The natural valuation question — "what should team X pay for player Y?" — can therefore be reframed: given the team's existing playing XI's cumulative $\bar{\Delta}$, and the marginal increase player Y would provide, the auction bid should reflect the expected wins this marginal increase converts into.

7.2 Player of the match

A formal player-of-the-match award is, by definition, the player with the highest Δ_p in that match. The framework also supports more nuanced awards: highest powerplay delta, highest death-over delta, etc.

We computed POM by maximum Δ_p for the 2024 IPL final and several knockout matches; the delta-derived POM agreed with the official award in approximately 60% of cases. The remaining 40% reveal a consistent bias: official POM voting overweights high-strike-rate cameos and underweights batters who anchored powerplays at modest strike rates against high-quality new-ball attacks.

7.3 Team selection

The team-selection question — which playing XI from a 25-player roster maximizes expected match delta? — becomes a constrained optimization problem with delta as the objective and the usual constraints (one wicket-keeper, four overseas players, sufficient bowling depth). The optimization is straightforward; what changes with delta is that the all-rounder question ("do we play a second specialist or an extra all-rounder?") is answered cleanly: pick the eleven players with highest cumulative $\bar{\Delta}_p$ subject to the structural constraints. In this formulation, the traditional heuristics for team-construction — "we need an anchor at three," "we need a sixth bowler," "we need a finisher who can clear the rope at the death" — are not augmented but *replaced* by a direct maximization of expected contribution under the constraints. The role labels become observed properties of the optimum (a player who tops the cumulative-delta solution will turn out to bat at three because his powerplay-and-middle delta is large) rather than constraints imposed beforehand.

7.4 Talent identification and scouting

Per-ball delta, computed across a domestic season, identifies young players whose ball-level contribution exceeds replacement level by a wider margin than their headline statistics suggest. The IPL 2026 emergence of Anshul Kamboj (62.2 total Δ in his first full season) is exactly the kind of signal a delta-based scouting system would have flagged from his prior domestic numbers, where his strike rates and economy rates alone might not have stood out.

8 Discussion and Limitations

8.1 Par-score model assumptions

Our par-score model is empirical and unconditioned: $g(b, w)$ ignores match context (target, venue, opposition), team strength, and within-innings fatigue. A more sophisticated model would condition on these. We did not pursue this because (a) the simple model is interpretable and reproducible; (b) the conditioning variables introduce overfitting risks at the per-state granularity needed for delta computation; (c) most of the analytic conclusions in this paper are robust to the simplification, since the comparison across players is normalized and constant level-shifts in the par-score function cancel in the delta computation. Appendix A.3 quantifies the venue-mix bias for top players in our cohort and shows that even at the *level* of expected innings total, biases are modest (range -6 to $+7$ runs) and largely cancel in delta.

A reasonable next step is to validate sensitivity by re-computing all results with a Bayesian smoothed par-score model (e.g., Gaussian process regression on (b, w)) or with venue-conditioned par-score curves to bound the second-order effect from venue-specific shape variation. We expect the player rankings to be largely unchanged.

8.2 Second-innings projection

We use a single par-score model for both first and second innings. In a second innings with a target, the projected total is bounded above by the target plus a small buffer, and the optimization a batter faces changes accordingly. A complete framework would have a separate second-innings par-score model conditioned on the target. As a partial robustness check on whether this distorts our rankings, we compute first-innings-only versions of each player's average match delta and compare to the all-innings versions in Appendix A. The top of the table is largely preserved (Klaasen, Bumrah, Kohli, Chakravarthy all in their respective top five under both versions) but mid-tier rankings shift more, partly because first-innings sample sizes are small (5–20 matches per player). Separating sample-size noise from genuine second-innings model bias requires a target-conditioned second-innings model, which we identify as the natural sequel to this work.

8.3 Decoupling delta from the projection

The Delta framework as defined in this paper computes per-ball changes in projected innings total. The framework itself, however, is decoupled from this specific choice of projected quantity: any state-based projection that admits a counterfactual at adjacent ball-states can be plugged into equation 1 to yield a delta. A natural alternative is to use win probability rather than projected runs, in direct analogy with Win Probability Added in baseball tango2007. Win-probability delta would capture two things runs-delta does not. First, it inherently handles the optimal-stopping structure of a chase: a batter playing well when his team is already comfortably ahead receives a large runs-delta but a small win-probability delta, the latter reflecting his actual contribution to changing the outcome rather than to padding the runs differential. Second, win-probability delta admits a clean and meaningful pre-match anchor that runs-delta does not. The iterative version of runs-delta already captures opposition quality at the ball level: a run scored off Bumrah is credited more than a run scored off a weaker bowler, because the fixpoint iteration propagates opposition strength through the recursion. What runs-delta does not capture is pre-match expectation. A player taking his team from a 10% pre-match win probability against a stronger side to victory has accomplished something materially different from a player taking his team from a 70% baseline to victory against a weaker side, even if their per-ball matchups were identical.

The choice of pre-match anchor is itself a methodological commitment. The standard Win Probability Added formulation in baseball uses a 50–50 anchor and inherits exactly the limitation we describe here: it counts every run-scoring action's impact against an idealised even matchup, not against the team's actual pre-game expectation. The magnitude of distortion is smaller in baseball than in cricket because pre-game team-strength variance is bounded (no MLB team is dominantly favoured against another) and because a 162-game season averages much of it out; sabermetric variants such as Championship WPA address it explicitly via prior anchoring. In T20 cricket — and especially in international cricket, where pre-match strength differences are large and the toss is non-trivial — the principled choice is a calibrated prior derived from an Elo-style team rating with toss and venue adjustments. We treat prior-anchored win-probability delta, integrated with the target-conditioned second-innings model of the previous subsection, as the central direction for the next paper in this line.

8.4 Variance and small-sample issues

Per-ball delta has high variance — a single boundary or wicket can produce a delta of ±10 runs — so player-level averages are noisy at fewer than 10–15 matches. We have applied a 10-match minimum throughout. A bowler like Donovan Ferreira, with 8 matches and a per-match average of 18.9, would top our table by per-match average if not filtered; at that workload we cannot distinguish skill from variance.

9 Conclusion

Delta gives cricket a single, role-independent measure of player contribution that traditional metrics cannot. Implementing it on four years of IPL ball-by-ball data and computing per-player aggregates for the current era yields a leaderboard that confirms intuitive judgments (Bumrah dominant; Klaasen specialized to the middle overs; Kohli's role narrowed to powerplay accumulation) and refines them where intuition is wrong (Hardik Pandya as the most negative all-rounder by net delta; Sunil Narine as the only genuinely positive two-way contributor). Year-over-year delta also tracks the well-known regression of breakout bowlers cleanly, with Noor Ahmad's three-season arc as the sharpest recent example. The iterative version of delta, structurally analogous to PageRank's eigenvector iteration, meaningfully reorders the rankings for high-leverage players and is now computationally cheap to compute.

This paper develops Delta, a leverage-weighted contribution metric for T20 cricket, into a fully specified and empirically validated framework. The contributions are: (i) an empirical par-score model trained on four IPL seasons and a formal invariance result establishing the robustness of player rankings to additive shifts in the projection function; (ii) per-player delta tables for IPL 2024–2026 across 43,368 deliveries and 450 player records, including phase-conditioned and iterative opposition-adjusted versions; (iii) a Spearman-correlation-based first-innings robustness check and a venue-mix bias quantification, both flagging the unconditioned par-score model as the most pressing limitation and a target-conditioned second-innings extension as the natural sequel; and (iv) a structural framing that places cricket player evaluation in the same family as Win Probability Added in baseball and Expected Possession Value in basketball, with the iterative version computing a fixpoint structurally analogous to PageRank. In aggregate, the framework gives cricket a single, role-independent unit in which to denominate the contribution of every ball.

Code and Data Availability

The empirical par-score table, the per-ball delta records, the per-player aggregates (including phase-conditioned and iterative opposition-adjusted versions), the venue-mix bias quantification, and all analysis scripts are released with the paper.

The ball-by-ball data used here was drawn from a relational database ingesting commercial IPL feeds, which provide enriched fields including stroke type and dismissal context. However, all core results in this paper — the par-score model, the per-ball deltas, the phase decomposition, the iterative opposition-adjusted version, the year-over-year arcs, the confidence intervals in Appendix A, and the venue-mix bias of Appendix A.3 — depend only on a small set of standard ball-by-ball fields: match identifier, innings number, over and ball number, runs (separately legal runs and extras), wicket flag and dismissal type, striker and bowler identifiers, and batting and bowling team. Every one of these fields is available in the publicly released Cricsheet ball-by-ball dataset cricsheet, which covers IPL matches from 2008 onward in YAML, JSON, and CSV formats under a free-to-use license. Any researcher can therefore reproduce the central analyses of this paper directly from Cricsheet without access to a commercial feed. The richer commercial fields (stroke type, dismissal-context fielding annotations) are required only for descriptive subsections such as the wicket-type breakdown of Noor Ahmad's 2025 dismissals; the framework itself is reproducible end-to-end from public data.

Acknowledgments

We thank our colleagues at Unicorns AI — Amol Desai, Rakesh Misra, Sreenath Krishnan, and Vignesh Subramanian — for the data infrastructure, engineering support, and ongoing discussions that shaped this work. We also thank reviewers and colleagues whose feedback substantially improved the framing, the formal invariance result, and the robustness analyses presented here.

A Robustness Checks

A.1 Confidence intervals on average match delta

The per-ball variance of delta is large — a single boundary or wicket can contribute ±10 runs of delta to a player's match total — which translates into appreciable standard errors on per-match averages even at our 10-match minimum. Table 7 reports the point estimate, within-player standard deviation, and 95% confidence interval (using a normal approximation, $\bar{\Delta} \pm 1.96 \cdot \mathrm{SD}/\sqrt{N}$) for the top 15 batters and top 12 bowlers in our cohort.

The CIs reveal substantial overlap between adjacent players. Bumrah's lower bound (4.69) does not exceed Chakravarthy's upper bound (12.52), so the two are not statistically separated by their per-match means alone at conventional thresholds. The same is true of nearly every adjacent pair in the table. This is not a defect of the metric — it is a reflection of the high per-ball variance of delta combined with the moderate per-player sample sizes.

The substantive comparative claims in this paper are therefore not safely resting on per-match point estimates alone. They rest on:

- *Multidimensional separation.* Bumrah is the only top-15 bowler with a substantially positive delta in all three phases (PP, middle, death). This joint condition is robust to the per-phase variance because the chance of simultaneous positivity in all three phases by noise alone is small. Similarly, Klaasen's specialism in the middle overs (6.79 of his 8.07 per-match

Table 7: Average match delta with 95% confidence intervals.

Player	Matches	Mean Δ	SD	95% CI
Batters:				
Heinrich Klaasen	36	8.07	15.19	[3.11, 13.04]
KL Rahul	35	7.81	19.89	[1.22, 14.40]
Tilak Varma	33	6.96	18.96	[0.49, 13.43]
Virat Kohli	38	6.44	13.98	[2.00, 10.89]
Suryakumar Yadav	34	6.13	15.43	[0.95, 11.32]
Rajat Patidar	34	6.00	14.13	[1.25, 10.75]
Sai Sudharsan	35	5.40	15.75	[0.18, 10.62]
Tim David	27	5.34	11.20	[1.12, 9.57]
Tristan Stubbs	33	5.17	12.96	[0.75, 9.59]
Travis Head	35	4.64	21.39	[–2.45, 11.73]
Sanju Samson	32	4.45	21.39	[–2.96, 11.86]
Shreyas Iyer	37	4.14	18.01	[–1.66, 9.95]
Bowlers:				
Jasprit Bumrah	32	11.19	18.77	[4.69, 17.69]
Mohsin Khan	14	8.78	30.25	[–7.07, 24.62]
Josh Hazlewood	17	7.79	19.97	[–1.70, 17.28]
Varun Chakravarthy	33	6.56	17.45	[0.61, 12.52]
Eshan Malinga	15	5.23	15.52	[–2.62, 13.09]
Prince Yadav	14	5.10	15.04	[–2.78, 12.98]
Anshul Kamboj	19	3.27	14.25	[–3.13, 9.68]
Trent Boult	34	3.12	18.94	[–3.25, 9.48]
Matheesha Pathirana	18	2.51	11.61	[–2.85, 7.87]
Bhuvneshwar Kumar	38	1.81	23.92	[–5.80, 9.41]
Noor Ahmad	32	1.70	15.66	[–3.72, 7.13]

delta from one phase) is robust as a phase-decomposition signature regardless of the absolute average.

- *Direction of effect, not magnitude.* The qualitative finding that Hardik Pandya's bowling delta is substantially negative (–199 over 35 matches, a per-match average of –5.7) is robust because the lower end of his CI is still negative.
- *Year-over-year arcs.* A within-player change of order 5–10 runs per match across consecutive seasons (as in the Noor Ahmad case) is large relative to the per-player CI width and remains a defensible empirical claim.

A natural next step is to compute hierarchical (partial-pooling) Bayesian estimates of player delta, which would tighten the per-player intervals by pooling toward a league mean. We do not pursue this here.

A.2 First-innings vs all-innings rankings

The unified par-score model treats first and second innings symmetrically, which is conceptually wrong for a chase (Section 8). To assess how much this distorts the rankings, we recompute average match delta using only first-innings deliveries for each player and compare to the all-innings version. The first-innings subsample is naturally smaller — typical first-innings counts per player are 5–25 matches, against 10–38 across both innings.

For the top 15 batters and 15 bowlers, the Spearman rank correlation between full-sample and first-innings-only average match delta is 0.44 for batters and 0.65 for bowlers. The correlations are positive but lower than one would expect under a hypothesis of perfect stability. A material part of the rank-shift, however, is small-sample noise: at $N \leq 10$ first-innings matches, a single high-impact match can shift a player's first-innings average by several runs.

Top-tier identity is mostly preserved across the two versions:

- Heinrich Klaasen is the top-1 batter under both versions.
- Bumrah is in the top-5 bowlers under both versions.
- Kohli, KL Rahul, Tilak Varma all remain in the top batter group.
- Chakravarthy remains in the top-5 bowlers.
- Hardik Pandya remains substantially negative under both versions.

Mid-tier rankings shift considerably. Mustafizur Rahman, with $N = 5$ first-innings matches, has a first-innings average of +14.86 versus a full-sample average of +3.15; this is almost certainly a small-sample artifact rather than a genuine bias correction. Eshan Malinga's first-innings average of −0.73 ($N = 4$) versus a full-sample +5.23 likewise reflects small-sample variance.

We interpret this analysis as setting an upper bound on the magnitude of unified-model second-innings distortion: the rank shifts are real but are entangled with first-innings-only sample-size noise that we cannot fully separate without a target-conditioned second-innings model. We flag this as the most pressing direction for future work.

A.3 Venue and pitch heterogeneity

A second concern about the unconditioned par-score model is that scoring patterns differ substantially across IPL venues. Eden Gardens and the Arun Jaitley Stadium average around 197–201 runs per first innings; M.A. Chidambaram Stadium (Chepauk) averages 168. The same +5 delta on a Chepauk pitch and a Delhi pitch represents arguably different underlying contributions, since the par-score curves have different shapes.

To quantify the magnitude of this concern, we compute for each top player a *venue-mix bias*: the difference between the venue-weighted average first-innings total of his matches and the league mean (183.2 in our training data). Table 8 reports the result for selected top players.

The full distribution across 28 top players ranges from −6.1 (Pathirana) to +7.0 (Russell), with median +1.4. The pattern is intuitive: KKR players (Russell, Narine, Chakravarthy) play disproportionately at high-scoring Eden Gardens; CSK players (Pathirana, Jadeja, Kamboj) at low-scoring Chepauk; DC players (Stubbs) at high-scoring Arun Jaitley.

These biases are however biases in the *level* of the par-score function for each player's venue mix, not in delta. Delta is a difference of two projected totals at adjacent states. A par-score function that is uniformly shifted by a constant venue offset Δ_v produces the same per-ball delta as the unshifted version: $T_k - T_{k-1} = [s_k + g(b_k, w_k) + \Delta_v] - [s_{k-1} + g(b_{k-1}, w_{k-1}) + \Delta_v]$, with the Δ_v terms cancelling out. The same monotone-transformation argument we made in Section 4.3 applies again here: any par-score function that is monotone and that differs from ours by a player-independent transformation produces the same delta rankings.

What is *not* fully bounded by this argument is venue-specific *shape* variation in the par-score curve — if Chepauk pitches concentrate run-scoring opportunity in different regions of the (balls-left, wickets-in-hand) state space than Wankhede, the difference structure will not perfectly cancel.

Table 8: Venue-mix bias in expected innings total for selected top players, IPL 2024–2026.

Player	Matches	Venue-wtd par	Bias vs league mean (183.2)
Andre Russell	25	190.2	+7.0
Tristan Stubbs	34	190.0	+6.9
Sunil Narine	33	188.6	+5.5
Varun Chakravarthy	33	187.9	+4.8
Sai Sudharsan	35	187.0	+3.8
KL Rahul	35	186.6	+3.4
Virat Kohli	38	186.5	+3.4
Eshan Malinga	15	186.3	+3.2
Heinrich Klaasen	36	185.5	+2.4
Travis Head	35	185.6	+2.5
Tilak Varma	33	182.0	–1.2
Suryakumar Yadav	34	181.4	–1.8
Hardik Pandya	35	181.5	–1.6
Trent Boult	34	181.6	–1.5
Jasprit Bumrah	32	182.3	–0.8
Noor Ahmad	32	180.2	–2.9
Anshul Kamboj	19	179.6	–3.6
Ravindra Jadeja	35	179.0	–4.2
Mohsin Khan	14	178.6	–4.5
Matheesha Pathirana	18	177.1	–6.1

We suspect this second-order effect is small for IPL-grade venues, where the basic dynamics of T20 batting (front-load powerplay, accelerate at the death) are similar across venues, but a venue-conditioned par-score model would be required to bound it formally. We treat this, alongside target-aware second-innings modeling, as a v3 priority.

References

[1] Anand Rajaraman and Vishal Misra. *Delta: A Uniform Measure of Player Contributions in Cricket*. Working paper, June 2022.

[2] Tom Tango, Mitchel Lichtman, and Andrew Dolphin. *The Book: Playing the Percentages in Baseball*. Potomac Books, 2007.

[3] Daniel Cervone, Alex D'Amour, Luke Bornn, and Kirk Goldsberry. *A Multiresolution Stochastic Process Model for Predicting Basketball Possession Outcomes*. Journal of the American Statistical Association, 2016.

[4] Hermanus H. Lemmer. *A measure of the current batting abilities of cricket players*. South African Journal for Research in Sport, Physical Education and Recreation, 2004.

[5] Frank Duckworth and Tony Lewis. *A Fair Method for Resetting the Target in Interrupted One-Day Cricket Matches*. Journal of the Operational Research Society, 1998.

[6] Steven E. Stern. *The Duckworth-Lewis-Stern method: Extending the Duckworth-Lewis methodology to deal with modern scoring rates*. Journal of the Operational Research Society, 2016.

[7] John Davis, Harsha Perera, and Tim B. Swartz. *A simulator for Twenty20 cricket*. Australian & New Zealand Journal of Statistics, 2015.

[8] Sergey Brin and Lawrence Page. *The Anatomy of a Large-Scale Hypertextual Web Search Engine*. Computer Networks and ISDN Systems, 1998.

[9] Jon Kleinberg. *Authoritative Sources in a Hyperlinked Environment*. Journal of the ACM, 1999.

[10] Stephen Rushe. *Cricsheet: ball-by-ball cricket data*. Available at `https://cricsheet.org`.