

Performance Evaluation and Ranking of T20 International Bowlers Using Multi-Criteria Decision Analysis

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DOI: <https://doi.org/10.63163/jpehss.v4i2.1404>

Abstract

The rapid evolution of Twenty20 International (T20I) cricket has increased the demand for advanced sports analytics, shifting emphasis from traditional isolated statistics toward comprehensive multi-criteria evaluation frameworks. While batting performance metrics have received substantial attention in contemporary sports literature, robust and context-aware analytical frameworks for evaluating elite international bowling performance remain limited. This study addresses this gap by conducting a comprehensive data-driven performance evaluation of 19 top-ranked T20I bowlers using a dataset comprising $N = 2,812$ valid delivery-level observations. Grounded in a Multi-Criteria Decision-Making (MCDM) framework, this study developed a composite Bowler Performance Index (BPI) integrating normalized performance indicators, including wicket-taking ability measured through Wicket Percentage ($w_1 = 0.40$), pressure generation through Dot Ball Percentage ($w_2 = 0.35$), and run containment through Economy Rate ($w_3 = 0.25$). Contextual and structural phase analysis using χ^2 -based profiling revealed a specialized distribution of bowling responsibilities across different match phases. Spin bowlers primarily dominated the middle overs to restrict scoring opportunities, whereas front-line pace bowlers carried greater workloads during high-pressure Powerplay and Death-over phases. Arshdeep Singh recorded the highest workload with 214 deliveries and 79 dot balls, although his aggressive bowling approach also resulted in the highest extras conceded (22). In contrast, the final BPI rankings identified Gudakesh Motie (0.76) and Lockie Ferguson (0.72) as the most effective bowlers because of their superior balance between economy and wicket-taking efficiency. High-workload strike bowlers such as Arshdeep Singh (0.71) closely followed, suggesting that successful bowling performance in modern T20I cricket depends on achieving an effective balance between run restriction and wicket-taking capability. The findings demonstrate that the proposed framework provides a transparent and empirically robust approach for evaluating bowling performance across varying tactical roles and workloads. The model offers practical implications for coaches, selectors, and sports analysts by supporting player assessment, tactical planning, and evidence-based decision-making in international T20 cricket.

Introduction

Limited-overs cricket, particularly One Day International (ODI) and Twenty-20 (T-20) formats, has experienced substantial growth in global popularity over recent decades. Characterized by rapid pace and compressed timelines, these formats place considerable importance on each delivery, making advanced cricket analytics increasingly valuable for improving team performance, generating tactical insights, and supporting empirical sports research [1,2]. Modern match environments require analytical frameworks capable of accurately evaluating and ranking both teams and individual players. Consequently, performance indices integrating batting, bowling, and fielding contributions have emerged as important tools for understanding overall match impact. Multi-dimensional performance matrices are increasingly preferred over conventional statistics because they provide a more comprehensive assessment of on-field performance [3].

Within short-form cricket, bowling performance plays a particularly decisive role because of the limited number of deliveries and narrow margins for error. T20I cricket is inherently high-pressure, where bowling effectiveness is strongly influenced by a player's ability to create dot balls and secure wickets during critical phases of play [4]. However, conventional indicators such as bowling average and economy rate frequently fail to capture a bowler's complete contribution to match outcomes. To address these limitations, sports analytics has increasingly adopted quantitative approaches and Multi-Criteria Decision-Making (MCDM) frameworks for constructing holistic and transparent ranking systems [5–7].

The need for such integrated approaches arises because T20I success depends on multiple interconnected bowling factors, including dot-ball frequency, wicket-taking efficiency, phase-specific performance, and contextual match situations [8]. Single performance indicators often provide incomplete evaluations, whereas incorporating multiple variables produces more reliable measures of performance effectiveness [9]. MCDM provides a systematic mathematical framework for integrating competing performance criteria into a unified ranking system, thereby supporting player selection, tactical planning, and performance forecasting [10].

Previous studies have identified dot-ball accumulation, wicket-taking efficiency, and run containment as fundamental determinants of success in T20 cricket [11]. Researchers have consequently employed several MCDM techniques, including the Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Weighted Sum Method (WSM), and Weighted Product Method (WPM), to evaluate cricket performance. Existing applications have primarily focused on batting metrics or generalized player evaluations using indicators such as runs scored, strike rate, boundary frequency, and dot-ball percentage [12]. Similar approaches in franchise leagues such as the Indian Premier League (IPL) have demonstrated the effectiveness of multi-attribute ranking frameworks under varying weighting schemes [6].

Beyond traditional MCDM approaches, Data Envelopment Analysis (DEA), machine learning (ML), and hybrid computational models have also been applied to sports analytics. Studies employing DEA-based methods across multiple cricket formats have shown that integrated efficiency measures outperform isolated traditional metrics [4]. Similarly, machine learning approaches including random forests and logistic regression have identified phase-specific wicket-taking patterns and dot-ball frequency as major predictors of short-format match outcomes [15].

Despite these methodological advancements, important research gaps remain. Existing frameworks largely emphasize batting performance, captaincy evaluation, or general player assessment, while relatively little attention has been paid to specialized bowling evaluation models. Furthermore, much of the existing literature focuses on domestic franchise competitions such as the IPL or fantasy sports applications, creating a noticeable gap in analytical frameworks

for elite international bowling performance [13,16]. Previous reviews also indicate a lack of transparent ranking structures that integrate contextual variables with specialized bowling performance indicators within T20I cricket [17].

Therefore, this study addresses these gaps by developing a comprehensive framework to evaluate and rank international T20I bowlers using phase-specific performance indicators and a Multi-Criteria Decision-Making approach. Specifically, the study investigates key performance variables associated with bowling effectiveness and develops a context-aware analytical model designed to support more reliable and intelligent evaluation of elite T20I bowlers.

Research Design

This study adopts a quantitative and data-driven analytical framework to evaluate and rank Twenty20 International (T20I) bowlers. The methodology integrates descriptive statistical analysis, feature engineering, normalization techniques, and a weighted scoring model to develop a comprehensive performance evaluation system. The overall approach is grounded in a Multi-Criteria Decision-Making (MCDM) framework, in which multiple bowling performance indicators are integrated into a single composite performance measure.

Data Collection and Preprocessing

The dataset consists of ball-by-ball and aggregated bowling performance records of T20 International (T20I) bowlers extracted from ESPNcricinfo, a widely recognized and authoritative source of cricket statistics. A random sample comprising 30% of matches played by the top 19 ranked T20I bowlers was selected to improve representativeness while reducing potential sampling bias.

Each observation includes bowler identity (Bowler Name), match-phase information (Powerplay, Middle Overs, and Death Overs), delivery-level characteristics such as line, length, speed, and bowling variation, together with outcome variables including dot balls, runs conceded, wickets, and extras.

Data preprocessing involved removing missing and inconsistent records, standardizing categorical outcome labels, and aggregating ball-level observations into bowler-level summary statistics. Frequency-based contingency tables (cross-tabulations) were also constructed to examine relationships between bowling actions and match outcomes under varying conditions.

The final cleaned dataset consisted of **2,812 valid delivery-level observations** used for subsequent analysis.

Feature Engineering

To comprehensively evaluate bowling performance, several derived performance indicators were computed at the bowler level:

(a) Dot Ball Percentage

$$DotBall\% = \frac{\text{Dot Balls}}{\text{Total Balls}} \times 100$$

(b) Boundary Percentage

$$Boundary\% = \frac{\text{Fours} + \text{Sixes}}{\text{Total Balls}} \times 100$$

(c) Wicket Percentage

$$Wicket\% = \frac{\text{Dismissals}}{\text{Total Balls}} \times 100$$

(d) Runs Conceded

Runs were computed using weighted scoring of outcomes:

$$\text{Runs} = (1 \times \text{singles}) + (2 \times \text{doubles}) + (3 \times \text{triples}) + (4 \times \text{fours}) + (6 \times \text{sixes}) \\ + \text{extras} + \text{byes}$$

(e) Economy Rate

$$\text{Economy} = \frac{\text{RunsConceded}}{\text{TotalBalls}} \times 6$$

(f) Strike Rate

$$\text{StrikeRate} = \frac{\text{TotalBalls}}{\text{Wickets}}$$

(g) Bowling Average

$$\text{BowlingAverage} = \frac{\text{RunsConceded}}{\text{Wickets}}$$

These metrics collectively represent control ability, wicket-taking ability, and run suppression capability.

Phase-Based and Contextual Analysis

To capture match dynamics, bowling data was further segmented into:

- Powerplay overs
- Middle overs
- Death overs

A cross-tabulation approach was used to analyze:

- Bowler usage distribution across phases
- Outcome distribution per bowler
- Tactical role specialization (e.g., strike bowlers vs control bowlers)

This step enables identification of **context-dependent performance patterns**.

3.5 Normalization of Features

Since performance indicators operate on different scales, Min-Max normalization was applied to ensure comparability:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

To ensure consistency in interpretation, Economy Rate (where lower is better) was inverted prior to normalization:

$$\text{Economy}' = \max(\text{Economy}) - \text{Economy}$$

Normalized features included:

- Wicket Percentage
- Dot Ball Percentage
- Adjusted Economy Rate

Hybrid Performance Score Construction

A weighted linear scoring model was developed to compute an overall Bowler Performance Index (BPI).

$$\text{BPI} = w_1(\text{Wicket}\%) + w_2(\text{DotBall}\%) + w_3(\text{Economy}')$$

Where weights were defined as:

- $w_1 = 0.40$ (Wicket importance)
- $w_2 = 0.35$ (Dot ball pressure creation)
- $w_3 = 0.25$ (Economy contribution)

This weighting scheme reflects the strategic importance of wicket-taking in T20 cricket, followed by pressure-building dot balls and run suppression.

Ranking Procedure

Bowlers were ranked based on descending values of the Bowler Performance Index (BPI). A dense ranking method was used to ensure no gaps in rank assignment.

$$Rank(bowler_i) = f(BPI_i)$$

This produced a hierarchical classification of bowlers into:

- Elite performers
- Balanced performers
- Lower-performing bowlers

Results and Discussion

Bowler Name	Matched Played	Total Balls Bowled
Adam Zampa	7	151
Adil Rashid	5	108
Akeal Hosein	8	157
Anrich Nortje	7	164
Arshdeep Singh	8	214
Axar Patel	8	134
Fazalhaq Farooqi	6	121
Gudakesh Motie	5	97
Jofra Archer	5	107
Josh Hazlewood	7	169
Lockie Ferguson	5	123
Maheesh Theekshana	6	143
Mitchell Santner	6	151
Mustafizur Rahman	8	203
Nathan Ellis	8	155
Rashid Khan	7	173
Ravi Bishnoi	7	159
Shaheen Shah Afridi	6	138
Tim Southee	6	145
Total	125	2812

In Table 1, the descriptive summary of 19 bowlers shows that they collectively participated in 125 matches and delivered 2,812 balls across what appears to be a T20 tournament. Arshdeep Singh, Mustafizur Rahman, Akeal Hosein, Axar Patel, and Nathan Ellis each played the most matches (8), but their bowling workloads differed substantially. Arshdeep Singh bowled a tournament-high 214 balls, reflecting a heavy reliance on him as a lead pacer, while Axar Patel bowled only 134 balls despite also playing eight matches, suggesting a primary role as a batting all-rounder with secondary bowling duties. Mustafizur Rahman followed closely with 203 balls, indicating a similarly heavy workload. At the lower end, Gudakesh Motie bowled the fewest balls (97) despite playing five matches, implying either limited bowling utilization or a part-time spin role. Among bowlers with seven matches, Rashid Khan (173 balls) and Josh Hazlewood (169 balls) carried notable loads, whereas Adam Zampa bowled slightly less (151 balls), possibly due to spin alternatives in his team.

Phase	Frequency	Percent
Middle Overs	1,261	44.80%
Powerplay	896	31.90%
Death Overs	655	23.30%
Total	2,812	100.00%

Table 2 presents the distribution of the 2,812 balls bowled across three match phases: Powerplay, Middle Overs, and Death Overs. The largest share of deliveries occurred during the Middle Overs (overs 7–15), which accounted for 1,261 balls, representing 44.80% of the total. This is expected, as this phase typically involves spin bowling and tight defensive strategies to restrict run-scoring in the middle of an innings. The Powerplay (first six overs) ranked second with 896 balls (31.90%), reflecting its importance for pace bowlers and early wicket-taking opportunities despite being the shortest phase in terms of overs. The Death Overs (final five overs) saw the fewest deliveries, 655 balls (23.30%) which is also anticipated given that this phase contains fewer total overs (typically overs 16–20) and often features only two or three specialist bowlers per innings.

Length	Frequency	Percent
Full Length	1,260	44.80%
Good Length	835	29.70%
Short	553	19.70%
Yorker	75	2.70%
Full Toss	49	1.70%
Back of a Length	30	1.10%
Bouncer	10	0.40%
Total	2,812	100.00%

Table 3 displays the distribution of bowling lengths across all 2,812 deliveries bowled in the tournament. The most frequently used length was full length, accounting for 1,260 deliveries (44.80%), nearly identical to the proportion of middle-overs balls in Table 2. This suggests bowlers consistently pitched the ball up to encourage driving and seek swing or seam movement. Good

length deliveries ranked second with 835 balls (29.70%), representing the conventional stock ball for most pacers to induce uncertainty in batters. Short deliveries followed with 553 balls (19.70%), indicating a moderate use of the short ball as a tactical variation rather than a primary length. Yorker, the most effective death-over delivery, was used only 75 times (2.70%), reflecting its high skill requirement and risk of becoming a full toss if poorly executed. Full tosses occurred 49 times (1.70%), largely unintentional, while back-of-a-length deliveries (30 balls, 1.10%) and bouncers (10 balls, 0.40%) were rare.

Line	Frequency	Percent
Wide Outside Off	1,001	35.60%
Outside Off Stump	654	23.30%
Middle Stump	504	17.90%
Outside Leg Stump	466	16.60%
Body Line	187	6.70%
Total	2,812	100.00%

Table 4 presents the distribution of bowling lines across all 2,812 deliveries. The most frequently used line was wide outside off stump, accounting for 1,001 balls (35.60%). This reflects a common T20 strategy of bowling wide of off stump to restrict scoring, force batters to reach for the ball, and create catching opportunities in the off-side field. Deliveries directed at outside off stump ranked second with 654 balls (23.30%), combining with wide outside off to total 58.90% of all deliveries aimed at or outside the off stump, demonstrating a clear preference for keeping the ball away from the batter's body. Middle stump deliveries followed with 504 balls (17.90%), often used as stock balls for spinners or when targeting the stumps directly. Outside leg stump accounted for 466 balls (16.60%), a surprisingly high figure given that leg-side bowling can be dangerous in T20s, though it may include attempted yorkers swinging down leg or deliberate angles from around the wicket. The least used line was body line (directed at the batter's torso or hips), with only 187 balls (6.70%), reflecting its limited role as a short-ball tactic rather than a primary line.

Variation Type	Frequency	Percent
Standard Delivery	1,543	54.90%
Slower Ball	382	13.60%
Flatter	166	5.90%
Inswinger	128	4.60%
Legbreak	125	4.40%
Googly	120	4.30%
Seam	84	3.00%
Bouncer	71	2.50%
Off-cutter	48	1.70%
Outswinger	40	1.40%
Yorker	38	1.40%
Skidding	34	1.20%
Orthodox	33	1.20%
Total	2,812	100.00%

Table 5 displays the distribution of bowling variations across all 2,812 deliveries. The overwhelming majority were standard deliveries (i.e., stock balls with no significant deviation or pace change), accounting for 1,543 balls (54.90%). This indicates that bowlers relied primarily on their core deliveries, using variations selectively as surprise tactics rather than as primary weapons. The most common variation was the slower ball, with 382 deliveries (13.60%), reflecting its importance in T20 cricket as a pace-changing tool to deceive batters looking to hit big shots. Flatter deliveries (166 balls, 5.90%) were largely used by spinners to rush batters onto the shot. Among swing and seam variations, inswingers (128 balls, 4.60%) were more than three times as common as outswingers (40 balls, 1.40%), suggesting bowlers favored bringing the ball back into the batter to attack the stumps or pad. Legbreaks (125 balls, 4.40%) and googlies (120 balls, 4.30%) appeared in nearly equal measure, indicating wrist-spinners employed their variations frequently. Seam movement (84 balls, 3.00%) and off-cutters (48 balls, 1.70%) were less common. Notably, yorkers were recorded as a variation only 38 times (1.40%), far fewer than in Table 3's length distribution—suggesting the classification in Table 5 may treat yorkers specifically as a variation type rather than simply a length. Bouncers (71 balls, 2.50%) appeared more frequently here than the 10 bouncers reported in Table 3's length analysis, indicating a classification discrepancy between the two tables that warrants clarification.

Outcome	Frequency	Percent
Dot Ball	967	34.40%
1 Run	923	32.80%
Four	254	9.00%
Out (Wicket)	189	6.70%
2 Runs	145	5.20%
Six	144	5.10%
Extras	110	3.90%
Bye	66	2.30%
3 Runs	14	0.50%
Total	2,812	100.00%

Table 6 presents the distribution of bowling outcomes across all 2,812 deliveries, providing insight into the balance between bowling dominance and batting productivity. Dot balls were the single most common outcome, occurring 967 times (34.40%), which reflects effective bowling pressure and field placements in T20 cricket. Singles ranked second with 923 deliveries (32.80%), indicating that batters frequently managed to rotate the strike rather than score boundaries. Boundaries included 254 fours (9.00%) and 144 sixes (5.10%), combining for 14.10% of all deliveries resulting in a boundary, a typical rate in modern T20 cricket. Wickets fell on 189 deliveries (6.70%), meaning approximately one in every 15 balls produced a dismissal, a healthy strike rate for bowlers collectively. Two runs occurred 145 times (5.20%), while three runs were rare at only 14 deliveries (0.50%), reflecting the difficulty of running three without overthrows. Extras (110 balls, 3.90%) and byes (66 balls, 2.30%) contributed to the total, with wides and no-balls likely comprising the extras category.

Bowler Name	1, 2, 3 Runs	Bye	Dot Ball	Extras	Four	Wicket	Six
Adam Zampa	72	0	33	1	14	12	19
Adil Rashid	37	1	39	6	8	8	9
Akeal Hosein	63	1	50	7	21	8	7
Anrich Nortje	49	3	69	8	18	10	7
Arshdeep Singh	60	3	79	22	25	18	7
Axar Patel	60	0	49	2	6	9	8
Fazalhaq Farooqi	46	4	43	3	16	5	4
Gudakesh Motie	43	3	31	1	4	10	5
Jofra Archer	40	0	40	5	11	8	3
Josh Hazlewood	56	6	73	2	20	6	6
Lockie Ferguson	49	6	44	4	3	10	7
Maheesh Theekshana	70	0	47	3	10	9	4
Mitchell Santner	76	1	41	7	9	5	12
Mustafizur Rahman	65	11	64	17	18	15	13
Nathan Ellis	55	5	58	7	17	10	3
Rashid Khan	74	9	60	5	8	14	3
Ravi Bishnoi	63	4	58	3	15	10	6
Shaheen Shah Afridi	42	4	49	3	18	12	10
Tim Southee	62	5	40	4	13	10	11

Table 7 provides a bowler-wise breakdown of outcomes across all 2,812 deliveries, revealing distinct performance profiles. Arshdeep Singh led in wickets with 18 dismissals, supported by 79 dot balls, though he also conceded 22 extras (the highest among all bowlers) and 25 fours, indicating occasional inconsistency. Mustafizur Rahman matched Arshdeep's wicket tally (15) closely while delivering 64 dot balls and conceding 17 extras, but he was the most expensive in terms of sixes conceded (13, tied with Mitchell Santner). Rashid Khan took 14 wickets with an impressive 60 dot balls and conceded only 8 fours and 3 sixes, reflecting excellent economy and control. Among spinners, Adam Zampa took 12 wickets but conceded 19 sixes—the highest in that category, suggesting he was targeted aggressively despite his wicket-taking ability. Mitchell Santner's 12 sixes conceded alongside only 5 wickets indicate a costly tournament for him. At the efficient end, Lockie Ferguson claimed 10 wickets while conceding only 3 fours (lowest among pacers) and 7 sixes, backed by 44 dot balls, demonstrating exceptional boundary prevention. Gudakesh Motie (10 wickets, only 4 fours conceded) and Axar Patel (9 wickets, 6 fours) also showed tight bowling. In terms of dot ball accumulation, Josh Hazlewood (73 dot balls), Anrich Nortje (69 dot balls), and Mustafizur (64 dot balls) led the pace attack, while Nathan Ellis (58 dots, 10 wickets) provided a balanced contribution.

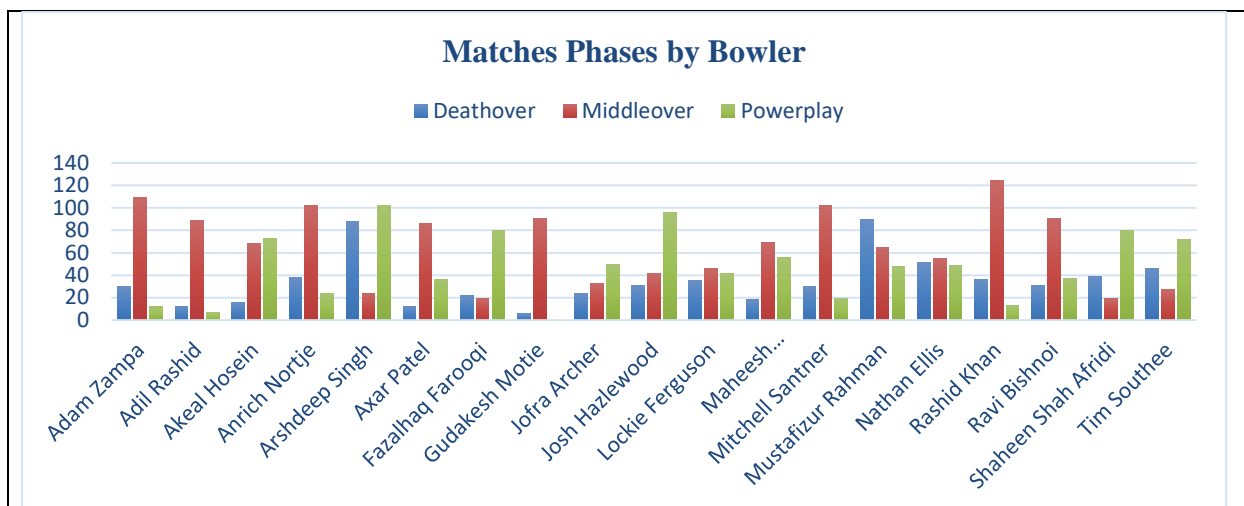


Figure 1: Matches Phases by Bowler

Figure 1 illustrates a specialized distribution of bowling workloads across the three match phases: Powerplay, Middle Overs, and Death Overs. Spin bowlers predominantly operated during the middle overs (overs 7–15), likely reflecting their role in restricting scoring and maintaining pressure during this phase. Rashid Khan (124 balls), Adam Zampa (109 balls), Mitchell Santner (102 balls), and Gudakesh Motie (91 balls) recorded their highest workloads during the middle overs. Conversely, front-line pace bowlers carried larger responsibilities during the Powerplay and Death phases. Arshdeep Singh (102 Powerplay balls; 88 Death balls), Mustafizur Rahman (48 Powerplay balls; 90 Death balls), and Josh Hazlewood (96 Powerplay balls; 31 Death balls) displayed substantial workloads in these high-pressure phases. Nathan Ellis exhibited a more balanced utilization profile, with deliveries distributed relatively evenly across Death (51), Middle (55), and Powerplay (49) overs, suggesting broader tactical flexibility.

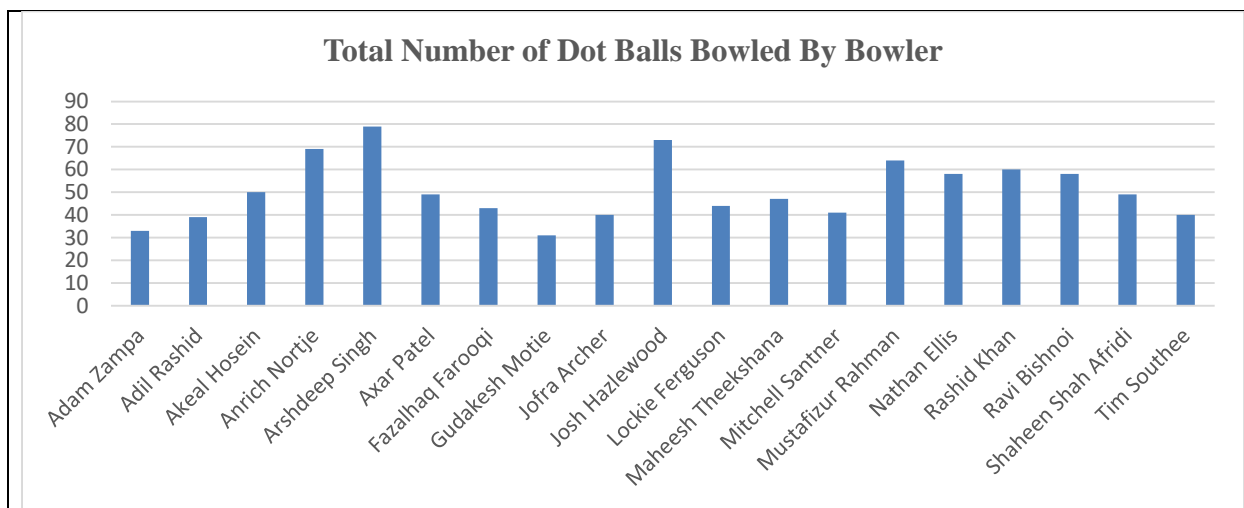


Figure 2: Total Number of Dots Balls Bowled by Bowler

Figure 2 presents the total number of dot balls delivered by the 19 bowlers, representing an important indicator of sustained bowling pressure. Arshdeep Singh recorded the highest number of dot balls (79), followed by Josh Hazlewood (73) and Anrich Nortje (69). These findings suggest strong effectiveness in restricting scoring opportunities. A moderate-performing group consisted of Mustafizur Rahman (64), Rashid Khan (60), Nathan Ellis (58), Ravi Bishnoi (58), and Akeal Hosein (50), all of whom consistently generated non-scoring deliveries. Conversely, Gudakesh

Motie (31) and Adam Zampa (33) recorded the lowest dot-ball counts, although their overall effectiveness may have been influenced by other performance dimensions such as economy and wicket-taking ability.

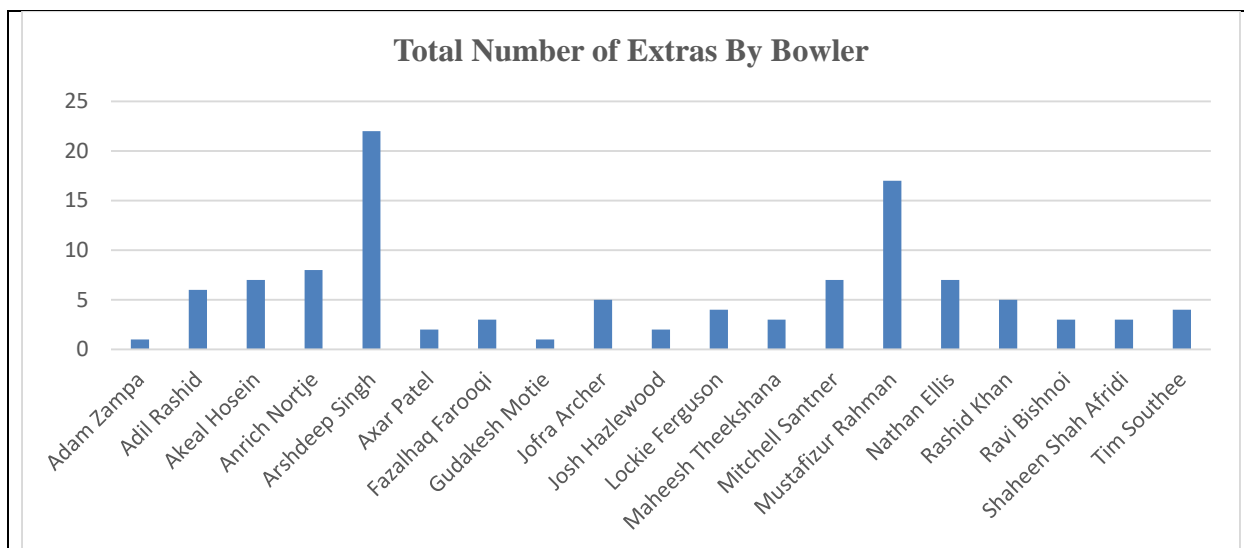


Figure 3: Total Number of Extras by Bowler

Figure 3 presents the total number of extras conceded by each bowler, representing potential indicators of bowling discipline and control. Arshdeep Singh recorded the highest number of extras (22), followed by Mustafizur Rahman (17), suggesting relatively greater variability in line and length consistency. Moderate levels of extras were observed for Anrich Nortje (8), Akeal Hosein (7), Mitchell Santner (7), and Nathan Ellis (7). In contrast, several bowlers maintained relatively low extra counts, including Gudakesh Motie (1), Adam Zampa (1), and Josh Hazlewood (2), reflecting comparatively stronger delivery control.

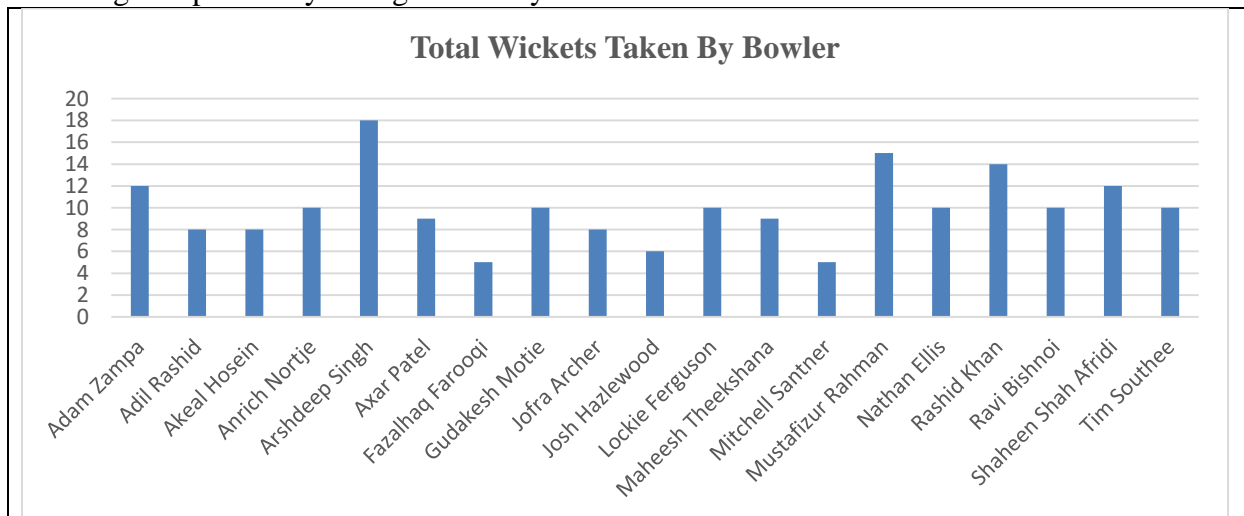


Figure 4: Total Wickets Taken by Bowler

Figure 4 illustrates the total wickets taken by the 19 tracked bowlers. Arshdeep Singh leads the field with 18 wickets, cementing his status as a premier strike option. Mustafizur Rahman (15) and Rashid Khan (14) follow closely, showcasing elite match-winning capabilities. A heavily populated mid-range includes bowlers like Adam Zampa (12), Shaheen Shah Afridi (12), as well as Nathan Ellis, Lockie Ferguson, and Ravi Bishnoi who all secured 10 dismissals. Conversely,

Mitchell Santner (5) and Fazalhaq Farooqi (5) recorded fewer wickets, pointing to a containment-heavy structural role within their respective sides.

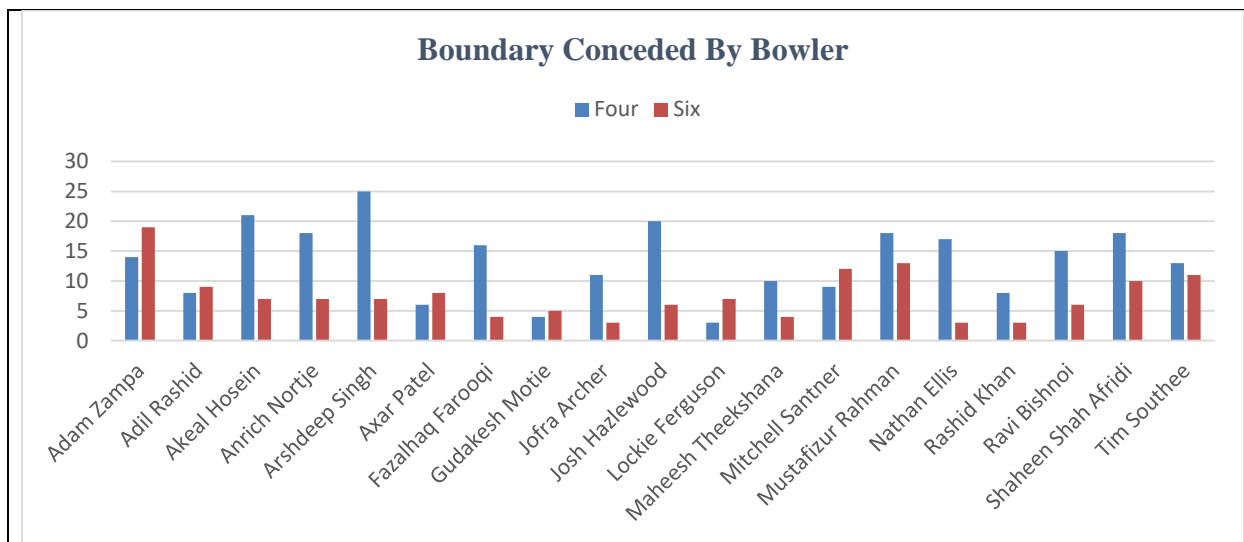


Figure 5: Boundary Conceded by Bowler

Figure 5 compares boundary concessions across bowlers through fours and sixes conceded. Arshdeep Singh conceded the highest number of fours (25), followed by Akeal Hosein (21) and Josh Hazlewood (20). Adam Zampa conceded the highest number of sixes (19), followed by Mustafizur Rahman and Mitchell Santner (13 each). Boundary patterns varied considerably among bowlers. Nathan Ellis conceded a relatively high number of fours (17) while restricting sixes to only 3. Gudakesh Motie (4 fours, 5 sixes), Rashid Khan (8 fours, 3 sixes), and Lockie Ferguson (3 fours, 7 sixes) demonstrated relatively strong boundary containment characteristics.

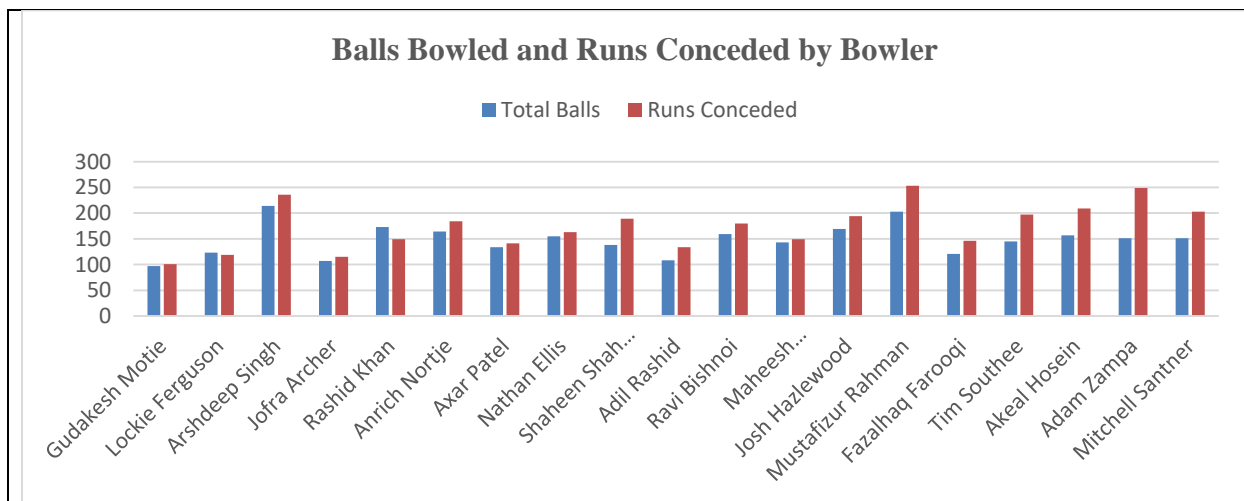


Figure 6: Balls Bowled and Runs Conceded by Bowler

Figure 6 compares bowling workload with runs conceded across the 19 bowlers. Arshdeep Singh carried the largest workload with 214 deliveries while conceding 236 runs. Mustafizur Rahman conceded the highest total runs (253) across 203 deliveries, reflecting both substantial workload and comparatively high run concession. Strong run-containment characteristics were observed for Rashid Khan (173 balls, 149 runs) and Lockie Ferguson (123 balls, 119 runs), who maintained favorable relationships between workload and runs conceded. Conversely, Adam Zampa (151

balls, 249 runs) and Mitchell Santner (151 balls, 203 runs) recorded comparatively higher run concessions relative to workload.

Ran k	Bowler Name	Econom y	Strik e Rate	Bowlin g Averag e	Dot Ball %	Boundar y %	Wicke t %	Performanc e Score
1	Gudakesh Motie	6.25	9.7	10.1	31.96	9.28	10.31	0.76
2	Lockie Ferguson	5.8	12.3	11.9	35.77	8.13	8.13	0.72
3	Arshdeep Singh	6.62	11.89	13.11	36.92	14.95	8.41	0.71
4	Jofra Archer	6.45	13.38	14.38	37.38	13.08	7.48	0.68
5	Rashid Khan	5.17	14.42	12.42	34.68	6.36	6.94	0.67
6	Anrich Nortje	6.73	16.4	18.4	42.07	15.24	6.1	0.66
7	Axar Patel	6.31	14.89	15.67	36.57	10.45	6.72	0.63
8	Nathan Ellis	6.31	15.5	16.3	37.42	12.9	6.45	0.62
9	Shaheen Shah Afridi	8.22	11.5	15.75	35.51	20.29	8.7	0.62
10	Adil Rashid	7.44	13.5	16.75	36.11	15.74	7.41	0.6
11	Ravi Bishnoi	6.79	15.9	18	36.48	13.21	6.29	0.57
12	Maheesh Theekshana	6.25	15.89	16.56	32.87	9.79	6.29	0.54
13	Josh Hazlewood	6.89	28.17	32.33	43.2	15.38	3.55	0.52
14	Mustafizur Rahman	7.48	13.53	16.87	31.53	15.27	7.39	0.52
15	Fazalhaq Farooqi	7.24	24.2	29.2	35.54	16.53	4.13	0.41
16	Tim Southee	8.15	14.5	19.7	27.59	16.55	6.9	0.39
17	Akeal Hosein	7.99	19.62	26.12	31.85	17.83	5.1	0.37
18	Adam Zampa	9.89	12.58	20.75	21.85	21.85	7.95	0.26
19	Mitchell Santner	8.07	30.2	40.6	27.15	13.91	3.31	0.18

Table 8 presents the final ranking of bowlers based on the composite Bowler Performance Index (BPI). Gudakesh Motie achieved the highest performance score (0.76), supported by a low

economy rate (6.25), strong bowling average (10.1), and effective boundary containment. Lockie Ferguson (0.72) and Arshdeep Singh (0.71) ranked second and third, respectively.

Rashid Khan recorded the most economical bowling performance (5.17), whereas Josh Hazlewood (43.20%) and Anrich Nortje (42.07%) produced the highest dot-ball percentages. However, despite generating strong pressure indicators, their overall rankings were affected by comparatively weaker strike rates and bowling averages.

At the lower end of the rankings, Adam Zampa (0.26) and Mitchell Santner (0.18) recorded the lowest performance scores. Santner registered the highest bowling average (40.6) and strike rate (30.2), while Zampa recorded the highest boundary percentage (21.85%), reducing their overall effectiveness within the composite evaluation framework.

Conclusion

This study developed a comprehensive multi-criteria analytical framework for evaluating and ranking elite T20 International (T20I) bowlers, addressing limitations associated with traditional single-metric performance measures. By integrating delivery-level data (N = 2,812) into an engineered Bowler Performance Index (BPI), the findings demonstrate that bowling effectiveness in modern T20 cricket cannot be adequately explained by a single performance indicator. Rather, successful bowling performance emerges from a balanced combination of wicket-taking ability, pressure generation through dot-ball creation, and effective run containment.

The empirical findings revealed a clear phase-specific specialization among contemporary international bowlers. Spin bowlers predominantly operated during middle overs, where their primary role involved restricting scoring opportunities and maintaining pressure. This pattern was evident in the substantial middle-over workloads observed among bowlers such as Rashid Khan and Adam Zampa. Conversely, fast bowlers carried significant responsibilities during both Powerplay and Death-over phases, which generally involve greater tactical complexity and higher performance demands.

The analysis further demonstrated that high-volume strike bowlers, including Arshdeep Singh and Mustafizur Rahman, generated substantial impact through wicket-taking and dot-ball production, although these contributions were accompanied by comparatively higher boundary concessions and extras. In contrast, bowlers such as Gudakesh Motie and Lockie Ferguson exhibited stronger overall efficiency by balancing wicket-taking effectiveness with run-control capabilities, resulting in superior BPI rankings.

Overall, the proposed multi-criteria scoring framework provides a transparent, interpretable, and empirically grounded alternative to conventional bowling evaluation methods. The framework accommodates differences in workload and tactical roles, thereby offering a more objective approach to player assessment in T20 cricket. From a practical perspective, the findings may support coaches, selectors, and cricket analysts in improving player evaluation, optimizing phase-specific strategies, identifying potentially undervalued bowling specialists, and strengthening evidence-based decision-making within international short-format cricket.

Future studies may extend this framework by incorporating contextual variables such as pitch conditions, opposition strength, match location, and match outcomes, as well as integrating machine learning approaches to enhance predictive performance and player evaluation accuracy.

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