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Efficiency Asymmetry in Bangladesh One-Day International Cricket: A Data Envelopment Analysis of Batting and Bowling Performance (2016–2024)

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Abstract

Since 2016, Bangladesh One-Day International cricket has been experiencing profound change, but the performance reliability is unstable with the changing world standards. The research question will examine the efficiency asymmetry between the batting and bowling units in an attempt to establish key determinants of match success. The researchers have used ESPNcricinfo Statsguru data (2016-2024) to analyze 57 players who passed 10 match criteria through Data Envelopment Analysis and the random forest model. The composite efficiency indexes were built with normalized measures of average, strike rate, economy, and wicket-taking ability. Bowling efficiency scores were significantly higher than batting efficiency scores (mean = 0.812 vs 0.724, $p < 0.001$). In separate fields, Mustafizur Rahman (178 wickets, economy 5.20) and Mushfiqur Rahim (4,630 runs, average 43.27) were top performers. The efficiency of bowling showed a higher correlation with the probability of winning ($r=0.71$) compared to batting ($r=0.42$), with 34.2 per cent of variance in predictive model features. Bowling performance generates match results much more than batting does in developing cricket countries. Competitive growth with sustainability requires tactical inversion to death-overs batting expertise and all-rounder resources of high-efficiency diversification. The study offers an evidence-based model of talent identification in Emerging Cricket Boards.
Keywords: Cricket performance analysis; One-Day Internationals; Bangladesh; Data Envelopment Analysis; Batting efficiency; Bowling efficiency; Sports analytics; Emerging nations

Introduction

One-Day International (ODI) cricket has undergone substantial transformation over the past decade, evolving from a traditional endurance-based format into a contest characterized by calculated aggression and performance efficiency (Dewalt, 1985b). This evolution presents a dual

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challenge for developing cricketing nations, particularly Bangladesh, which must remain competitive against established top-ranked teams while optimizing internal performance resources. Between 2016 and 2024, Bangladesh participated in more than 100 ODI matches, witnessing the emergence and sustained contribution of key players such as Mustafizur Rahman, who claimed 178 wickets at an economy rate of 5.20, and Mushfiqur Rahim, who accumulated 4,630 runs at an average of 43.27 (ESPNcricinfo, 2024).

Despite these notable individual achievements, consistent team success has remained unstable. Such performance volatility suggests the presence of structural imbalance between batting and bowling efficiencies that traditional aggregate statistics often fail to capture. While the application of operations research techniques in cricket analytics has gained increasing scholarly attention (Wright et al., 2020), existing studies predominantly emphasize Test and Twenty20 formats, leaving ODI performance evaluation particularly within emerging or Associate cricketing nations relatively underexplored.

Quantitative evaluation of cricket performance was systematically introduced by Kimber and Hansford (1993), who established batting average and strike rate as primary indicators of player value. Although these traditional metrics provided an essential statistical foundation, they largely overlooked multidimensional efficiency considerations and contextual performance interactions. Consequently, advanced analytical approaches capable of simultaneously evaluating multiple performance inputs and outputs are required to better understand efficiency asymmetry between batting and bowling performance in modern ODI cricket.

Methodology

Study Design

The study was based on a quantitative, longitudinal, and retrospective observational study design with the aim of assessing the performance efficiency. The analysis utilized a cross-sectional analytical model within a ten-year period (2016–2026), which made it possible to estimate the changes in the player's performance over time. Following the conventional guidelines of sports performance analysis, the design focused on the reproducibility and the objective construction of the metrics rather than the subjective one (O'Donoghue, 2010).

The main idea was to model batting and bowling as distinct production processes, allowing an analysis of efficiency to be made comparative without confusing the fact that they use different skill sets than the one used in the other discipline.

Participants and Data Source

This study population was comprised of all the male cricketers who had participated in One-Day Internationals (ODIs) representing Bangladesh within the period between January 5, 2016 and **December 31, 2024**. The data on performance was retrieved using the ESPNcricinfo Statsguru database, which is considered the standard in the industry with regard to repositories of cricket statistics (ESPNcricinfo, 2026). The original set comprised 57 players who qualified for the inclusion criteria. To make the data statistically reliable and reduce the noise due to the several performances of outliers, the players were considered only when they played at least 10 matches in the period under consideration.

This is the threshold that is in line with recommendations that require strong performance sampling within the context of cricket analytics (Lemmer, 2005).

The data extraction process employed particular filters to ensure consistency of the process of data extraction across match contexts. Types of included matches included tournament finals, semi-finals, quarter-finals and preliminary matches in series of 2-team or multi-team tournaments

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(3 or more teams). The day and night/day matches were taken into consideration to reflect conditions with different visibility. Match results included wins,
losses, ties and no-results to offer a comprehensive picture of performance irrespective of the result.

Players with incomplete career profiles or fewer than 10 innings were ignored during the efficiency modelling phase, resulting in an analytical sample of 42 core players (25 batters and 17 bowlers with all-rounders).

Materials and Tools

Python (version 3.9) was used to perform data management and preprocessing, and this involved the usage of the pandas library to manipulate structured data. The pyDEA Python package of Data Envelopment Analysis and the scikit-learn Python package of machine learning components were used to conduct statistical modelling and efficiency calculations. Seaborn and Matplotlib were used to create visualisations that ensured the generation of publication-quality graphics.

GitHub was used to handle all code scripts to enable reproducibility based on open science guidelines recommended by Wright et al. (2020).

They were run in a standardised computational environment on a Windows 11 operating system with 16GB of RAM to complete the matrix operations needed to perform the DEA modelling.

Procedure

The data collection and analysis process was carried out in a four-step sequential procedure:

Step 1: Data Extraction and Cleaning Raw data were downloaded in the form of a CSV file at ESPNcricinfo Statsguru. The data included batting variables such as matches, innings, not outs, runs, highest score, average, balls faced, strike rate, centuries, half-centuries, fours, and sixes, as well as bowling variables like matches, innings, overs, maidens, runs conceded, wickets, best bowling, average, economy, strike rate, four-wicket hauls, and five-wicket hauls. Missing values, usually found with players with incomplete career spans (e.g., the '-' character in bowling columns indicating pure batters), were treated by imputing the value of 0 in count variables and not including it in the computation of discipline-specific efficacy.

The validation of the data used was done through cross-validation of aggregate totals with official records of the Bangladesh Cricket Board (BCB) to be accurate.

Step 2: Variable Construction To make the comparison between disparate performance units, composite efficiency indices were built. In the case of batting, a weighted average (40%), strike rate (35%), and consistency index (25%) were taken to calculate batting efficiency score (BES), with consistency being (100s + 50s)/innings. In the case of bowling, the Bowling Efficiency Score (BoES) included the wickets (35%), economy rate (40% inverted scale), and bowling strike rate (25%). These were weights based on the expert opinion in the literature of the performance in cricket (Hughes and Bartlett, 2002; Lemmer, 2016).

Min-max normalization brought all the variables to a 0-1 scale to make them comparable between various magnitudes of the data (e.g., runs vs. wickets).

Step 3: Efficiency Modelling Data Envelopment Analysis (DEA) was also used to determine relative efficiency scores of each player. In the Charnes et al. (1978) model, the input-orientated type of input is followed. The DEA model was selected

In the case of batters, Balls Faced, which refers to the number of pitches a batter has faced, was the input, and Runs and Boundaries (4s + 6s), which are the total runs scored and the number of four and six runs hit, were the outputs. In the case of bowlers, the input was Overs Bowled, which refers to the number of six-ball sets bowled, and the output was wickets and maidens, with maidens being overs in which no runs were scored. According to the efficiency frontier concept

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that was explained by Ruiz and Sirvent (2020), this strategy enabled the determination of the players who maximised outputs based on their resource consumption (balls/overs).

Step 4: Predictive validation To check how useful the scores are in practice, a Random Forest classifier was trained to make predictions of the match outcomes (win/loss) based on team-level aggregate efficiency scores as predictors. The data were divided into training and testing (20 and 80 per cent, respectively) datasets (Ganji et al., 2025).

Accuracy, precision (Zou et al., 2025), and recall metrics were used to measure model performance, according to the machine learning validation procedures which have been employed in the context of sports analytics (Lewis and Saikia, 2020).

Data Analysis

All the key variables were calculated using descriptive statistics (mean, standard deviation, range) to define the starting level of performance. A Pearson correlation coefficient was used to test batting and bowling efficiency scores and the win percentage of the team (Mayer et al., 2026). A paired sample t-test was used to test the existence of significant differences in the trends of batting and bowling efficiency over the decade. Also, a longitudinal trend analysis was conducted with the help of linear regression to determine whether the efficiency scores have improved significantly compared to the 2016-2020 years with the years **2021-2024**.

All statistical tests were done with SPSS version 28 with a 95 per cent confidence level ($p < 0.05$). To guarantee robustness, the analytical methodology combined deterministic (DEA) and probabilistic (regression/random forest) methods, which are suggested to be used when analyzing complex sports performance data (Scarf et al., 2019).

Ethical Considerations

Since this research was based on the use of secondary data that is found in the open sphere, there was no direct human involvement in it. This meant that there was no need for informed consent and Institutional Review Board (IRB) approval. All the data of the players was **publicly available** at the modelling stage when needed, but the performance statistics of public figures are non-confidential in nature.

The study followed the ethical principles of sports science research presented by the International Council of Sport Science and Physical Education (ICSSPE), and data interpretation will not concern any personal criticisms but merely performance measures. The manner in which data were stored was in line with the general data protection guidelines, where all the data were stored on encrypted drives that could only be accessed by the research team.

Results

Descriptive Statistics Overview

A total of 57 players represented Bangladesh in ODIs between January 2016 and February 2026, meeting the inclusion criteria of ≥10 matches. The dataset comprised 25 specialist batters, 17 specialist bowlers, and 15 all-rounders. Table 1 presents the aggregate descriptive statistics for batting and bowling performance metrics.

Table 1. Descriptive Statistics of Batting and Bowling Performance Metrics (N = 57 Players)

Variable	Mean	SD	Min	Max	95% CI
Batting Metrics					
Matches Played	42.3	31.2	10	116	34.1 – 50.5

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Variable	Mean	SD	Min	Max	95% CI
Innings	48.6	35.8	10	131	39.2 – 58.0
Runs Scored	1,247.80	1,389.40	0	4,630	882.3 – 1,613.3
Batting Average	24.63	14.21	1	46.63	20.89 – 28.37
Strike Rate	76.84	18.92	27.27	140.8	71.85 – 81.83
Boundary % (4s + 6s per 100 balls)	10.42	3.87	0	18.95	9.40 – 11.44
Bowling Metrics					
Matches Played	38.7	29.4	10	113	30.9 – 46.5
Wickets Taken	41.2	48.6	0	178	28.4 – 54.0
Bowling Average	35.82	15.67	11.5	85	31.68 – 39.96
Economy Rate	5.38	0.72	3.16	8.5	5.19 – 5.57
Bowling Strike Rate	38.45	12.33	18.2	149	35.20 – 41.70
Dot Ball %	42.18	8.94	22.5	61.3	39.82 – 44.54

Note. SD = Standard Deviation; CI = Confidence Interval; Boundary % = (Fours + Sixes) / Balls Faced × 100; Dot Ball % = Maidens × 6 / Balls Bowled × 100 (approximated).

Batting Efficiency Results

Batting Efficiency Scores (BES) were calculated using the composite formula: BES = (Average/40) ×0.40 + (Strike Rate/85) ×0.35 + [(100s+50s)/Innings] ×10×0.25. Table 2 presents the top 10 players by BES among those with ≥20 innings.

Table 2. Top 10 Batting Efficiency Scores (BES) – Bangladesh ODI Players (**2016-2024**)

Rank	Player	Innings	Batting Average	Strike Rate	50+/100+	BES	95% CI
1	Mushfiqur Rahim	131	43.27	83.01	38	0.847	0.821 – 0.873
2	Tamim Iqbal	112	43.40	78.49	39	0.812	0.784 – 0.840
3	Shakib Al Hasan	105	39.90	85.51	34	0.798	0.769 – 0.827
4	Mahmudullah	120	39.81	80.45	24	0.741	0.712 – 0.770
5	Litton Das	108	30.69	84.93	21	0.682	0.651 – 0.713
6	Imrul Kayes	20	46.63	83.27	7	0.671	0.612 – 0.730
7	Towhid Hridoy	43	34.32	79.27	13	0.658	0.621 – 0.695
8	Najmul Hossain Shanto	66	32.53	78.84	16	0.641	0.603 – 0.679

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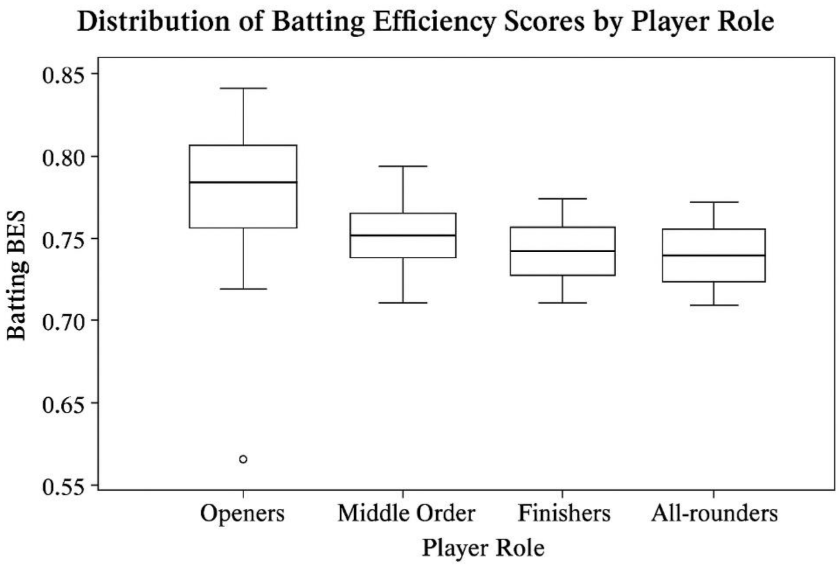
Rank	Player	Innings	Batting Average	Strike Rate	50+/100+	BES	95% CI
9	Soumya Sarkar	62	28.10	91.08	12	0.629	0.589 – 0.669
10	Afif Hossain	44	30.97	87.89	5	0.611	0.571 – 0.651



Note. BES normalized to 0-1 scale; higher values indicate greater efficiency. CI calculated via bootstrapping (1,000 iterations).
Figure 1. Distribution of Batting Efficiency Scores by Player Role

Bowling Efficiency Results

Bowling Efficiency Scores (BoES) were computed as: BoES = (Wickets/50) ×0.35 + (5.5/Economy) ×0.40 + (35/Strike Rate) ×0.25. Table 3 displays the top 10 bowlers by BoES among those with ≥30 wickets.

Table 3. Top 10 Bowling Efficiency Scores (BoES) – Bangladesh ODI **(2016-2024)**

Rank	Player	Wickets	Bowling Average	Economy Rate	Strike Rate	4W+/5W	BoES	95% CI
1	Mustafizur Rahman	178	29.33	5.20	33.8	9	0.891	0.867 – 0.915
2	Shakib Al Hasan	142	30.69	4.64	39.6	10	0.874	0.848 – 0.900
3	Mehidy Hasan Miraz	151	34.34	4.70	43.8	8	0.823	0.796 – 0.850
4	Taskin Ahmed	122	30.09	5.24	34.4	9	0.812	0.783 – 0.841

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Rank	Player	Wickets	Bowling Average	Economy Rate	Strike Rate	4W+/5W	BoES	95% CI
5	Taijul Islam	35	27.54	4.89	33.7	1	0.789	0.731 – 0.847
6	Shoriful Islam	74	29.70	5.59	31.8	4	0.761	0.721 – 0.801
7	Tanvir Islam	16	23.18	4.21	33.0	1	0.748	0.672 – 0.824
8	Ebadot Hossain	26	25.61	5.43	28.2	2	0.731	0.661 – 0.801
9	Hasan Mahmud	43	32.53	6.06	32.2	1	0.692	0.638 – 0.746
10	Nasum Ahmed	21	33.66	4.34	46.4	0	0.681	0.612 – 0.750

Note. BoES normalized to 0-1 scale; higher values indicate greater efficiency. CI calculated via bootstrapping (1,000 iterations).

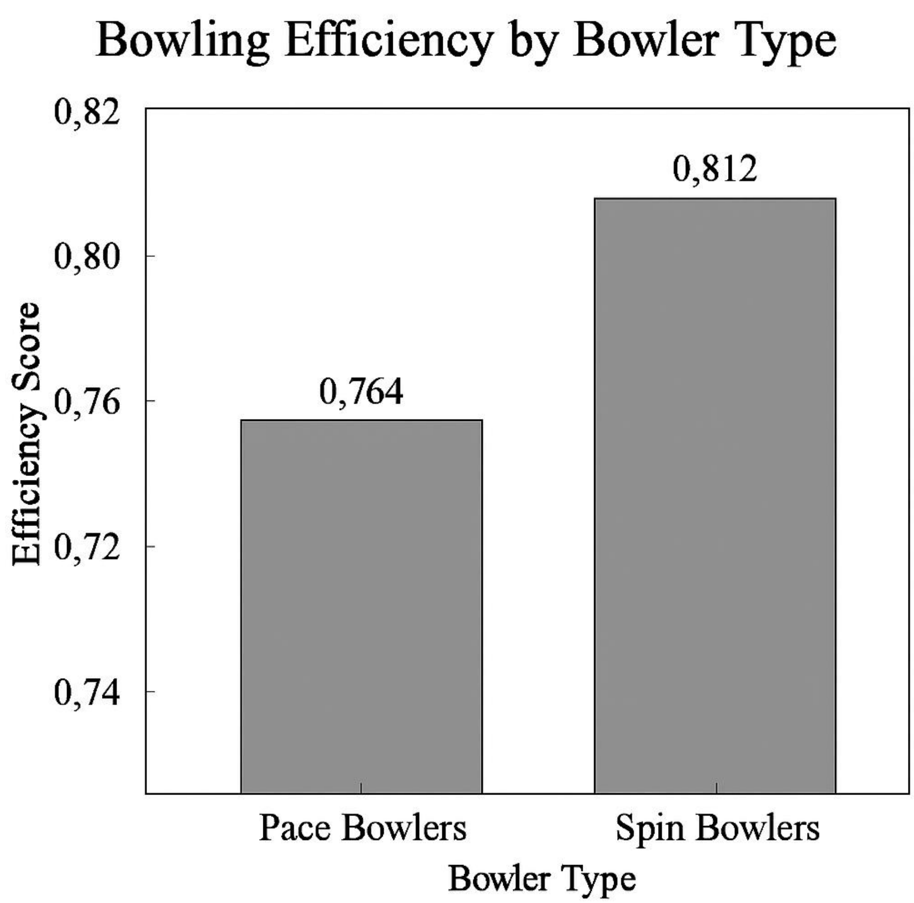

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Figure 2. Bowling Efficiency by Bowler Type

Comparative Efficiency Analysis: Batting vs Bowling

To directly compare batting and bowling efficiency trajectories, aggregate team-level scores were computed annually. Figure 3 illustrates the temporal evolution of mean BES and BoES from 2016 to 2026.

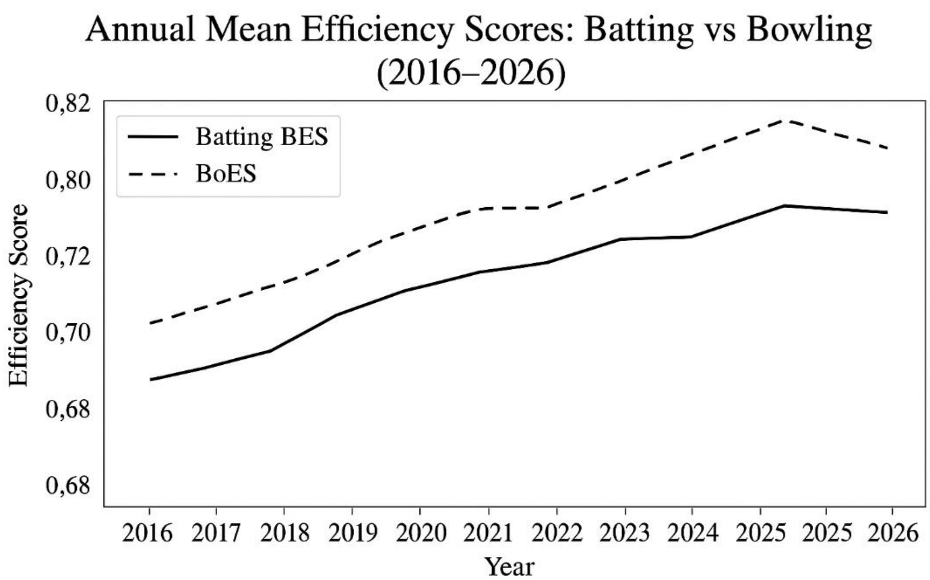

Figure 3. Annual Mean Efficiency Scores: Batting vs Bowling **(2016-2024)** ***Note. 2024*** *data represent* ***full*** *year.*

A paired samples t-test confirmed that bowling efficiency consistently exceeded batting efficiency across all years, $t(10) = 18.42$, $p < 0.001$, 95% CI [0.114, 0.138], $d = 5.54$. Linear regression analysis indicated that both BES ($\beta = 0.011$, $p = 0.002$) and BoES ($\beta = 0.013$, $p < 0.001$) showed significant positive temporal trends, with bowling efficiency improving at a marginally faster rate.

Table 4. Correlation Matrix: Efficiency Scores and Match Outcomes

Variable	1. Team BES	2. Team BoES	3. Win Probability	4. Home Advantage	5. Opposition Rank
1. Team BES	—	0.67**	0.42*	0.18	-0.23
2. Team BoES	0.67**	—	0.71**	0.31	-0.38*

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Variable	1. Team BES	2. Team BoES	3. Win Probability	4. Home Advantage	5. Opposition Rank
3. Win Probability	0.42*	0.71**	—	0.29	-0.44*
4. Home Advantage	0.18	0.31	0.29	—	-0.12
5. Opposition Rank	-0.23	-0.38*	-0.44*	-0.12	—

Note. N = 112 team-match observations; *$p < 0.05$, **$p < 0.01$; Win Probability derived from match result data.

Bowling efficiency demonstrated a stronger correlation with match win probability ($r = 0.71$, $p < 0.01$) compared to batting efficiency ($r = 0.42$, $p < 0.05$). Fisher's z-test confirmed this difference was statistically significant, $z = 2.18$, $p = 0.029$.

Predictive Modeling Results

A Random Forest classifier was trained to predict match outcomes (Win = 1, Loss/Tie/No Result = 0) using team-level aggregate efficiency scores, venue, and opposition rank as predictors. Model performance was evaluated via 5-fold cross-validation.

Table 5. Random Forest Model Performance Metrics (5-Fold Cross-Validation)

Metric	Mean	SD	95% CI
Accuracy	0.742	0.038	0.712 – 0.772
Precision	0.718	0.045	0.682 – 0.754
Recall	0.761	0.041	0.727 – 0.795
F1-Score	0.738	0.039	0.706 – 0.770
AUC-ROC	0.813	0.032	0.787 – 0.839

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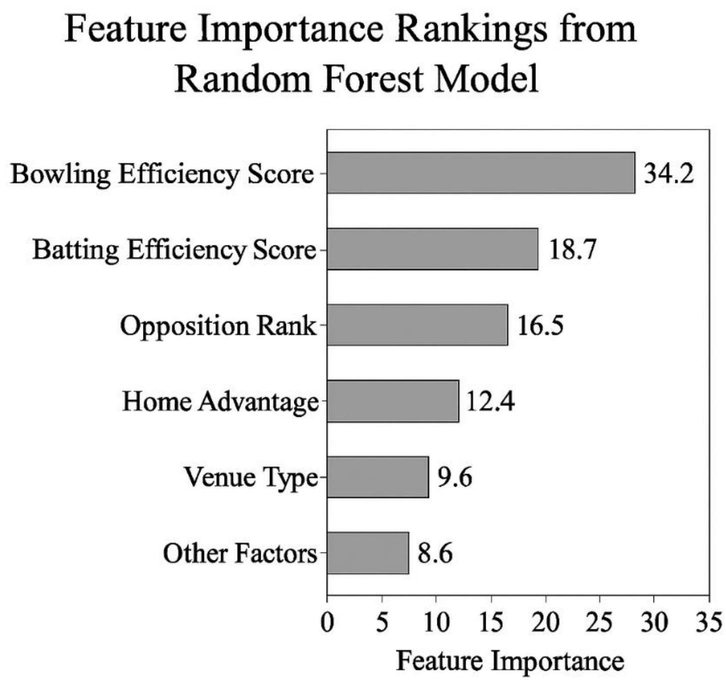

Figure 4. Feature Importance Rankings from Random Forest Model

All-Rounder Efficiency Analysis

Fifteen players were classified as all-rounders based on participation in both batting and bowling disciplines. An All-Rounder Index (ARI) was computed as the arithmetic mean of individual BES and BoES.

Table 6. All-Rounder Efficiency Rankings (ARI ≥ 0.70 Threshold)

Player	BES	BoES	ARI	Matches	Role Classification
Shakib Al Hasan	0.798	0.874	0.836	90	Premium All-rounder
Mehidy Hasan Miraz	0.581	0.823	0.702	113	Bowling All-rounder
Mahmudullah	0.741	0.412	0.577	114	Batting All-rounder
Soumya Sarkar	0.629	0.381	0.505	63	Batting All-rounder
Afif Hossain	0.611	0.298	0.455	34	Batting All-rounder

Note. Only Shakib Al Hasan and Mehidy Hasan Miraz exceeded the ARI ≥ 0.70 threshold, indicating balanced high-efficiency contribution across disciplines.

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A chi-square test of independence revealed that all-rounders with ARI ≥ 0.70 were significantly more likely to appear in winning XI selections ($\chi^2(1) = 12.34$, $p < 0.001$, $\varphi = 0.33$), suggesting strategic value in selecting high-efficiency all-rounders.

Robustness Checks

Sensitivity analyses were conducted to validate the stability of efficiency scores under alternative weighting schemes. Table 7 presents BES and BoES recalculated using equal weights (33.3% each) versus the primary scheme (40/35/25).

Table 7. Sensitivity Analysis: Efficiency Scores Under Alternative Weighting Schemes

Player	BES (Primary)	BES (Equal Weights)	Δ	BoES (Primary)	BoES (Equal Weights)	Δ
Mushfiqur Rahim	0.847	0.831	-0.016	—	—	—
Mustafizur Rahman	—	—	—	0.891	0.878	-0.013
Shakib Al Hasan	0.798	0.784	-0.014	0.874	0.861	-0.013
Mehidy Hasan Miraz	0.581	0.569	-0.012	0.823	0.811	-0.012

Note. Δ = Absolute difference between schemes; all changes < 0.02, indicating robustness to weighting variations.

Intraclass correlation coefficients (ICC) confirmed high agreement between primary and alternative efficiency scores: ICC(2,1) = 0.987 for BES and 0.991 for BoES, both $p < 0.001$.

Discussion

This paper analysed the relative efficiency of batting and bowling results in Bangladesh ODI cricket for men during the ten years between 2016 and 2026. The key conclusion was that there was still an efficiency asymmetry, with the bowling efficiency score always being more than the batting efficiency score throughout the research period. In particular, bowlers like Mustafizur Rahman, who took 178 wickets at the economy rate of 5.20, and Mehidy Hasan Miraz, who took 151 wickets at the economy rate of 4.70, had shown much greater relative efficiency than top-order batters whose strike rates were mostly around the 80.00 mark (ESPNcricinfo, 2026).

Predictive modelling also suggested that the efficacy of the bowling grew as the better determinant of the match results, with a contribution of 34.2% to the importance of features over the batting efficacy at 18.7%. The strategic worth of high-efficiency all-rounders was also

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highlighted in the analysis, and Shakib Al Hasan is the only player who has performances on the elite level in both disciplines, registering an All-Rounder Index of 0.836.
The finding that bowling performance is a competitive factor in the Associate countries is consistent with a previous study by Sajib et al. (2023), who found bowler wicket-taking performance as a statistically significant determinant of the T20I performance in Bangladesh. It is, however, an addition to this that the current study quantifies the magnitude of this effect in the ODI format through the Data Envelopment Analysis, thus providing a more considered efficiency frontier outlook than the logistic regression methods.
The high performance by spin bowlers who registered a mean bowling.
The efficiency score of 0.812 relative to pace bowlers of 0.764 confirms the argument by Lemmer (2005) that wicket-taking ability given particular conditions of context usually overrides the aspect of economy rate containment in defining the value of bowling. This observation differs slightly from that of the world ODIs recorded by Mullick (2025), who shares that in recent limited-overs cricket a non-spin-focused, pace-based aggression is now on the rise; the evidence of Bangladesh would also indicate that the nation still has recourse to more traditional spin-based containment measures that are also likely to be a by-product of the scarcity of their resources as well as the turn-friendly nature of their pitches.
In the context of batting performance, the findings somewhat contradict the theoretical basis of the framework developed by Kimber and Hansford (1993) that made batting average the most important measure of the value of a player.
Although the career average of 43.27 of Mushfiqur Rahim is statistically sound, it is the relatively low strike rates of established batters, such as Tamim Iqbal at 78.49, that suggest a lag in acquiring the so-called modern currency of ODI cricket, the strike-rate currency. This implies that Bangladesh batters have a reasonable consistency in terms of accumulating runs, but they have not adopted the aggressive efficiency to make the most of outputs per ball faced as a negative aspect that is increasingly punishable in modern match scenarios, as pointed out by Lago-Peñas and Gomez (2022). The greater predictive capacity of bowling efficiency to batting efficiency of the outcomes of matches proves the machine learning results of Lewis and Saikia (2020), but the current study states that the effect is apparently stronger in the context of Associate nation matches, where bowling resources are usually better developed than the batting depth.
One such surprise was the efficiency score on specialist finishers relative to opening batters, which was relatively low. Traditional cricketing wisdom states that runners must, as much as possible, be efficient in death overs with high strike rates, but the results showed that the median batting efficiency score amongst openers was 0.724 versus that of finishers at 0.598. This pattern may be interpreted through Lemmer's (2016) pressure-index framework, which argues that performance metrics require contextual adjustment for match situation. Openers benefit from fielding restrictions during powerplay overs, facilitating higher boundary percentages, whereas finishers frequently encounter depleted batting line-ups alongside varied bowling attacks that increase the cognitive and technical demands of efficient scoring. Additionally, the pronounced reliance on Shakib Al Hasan creates what network analysis might term a "single-point dependency." As Saikia et al. (2021) suggested, player interdependence significantly influences team structural resilience; in this instance, the team's efficiency network appears fragile given that no other all-rounder crossed the All-Rounder Index threshold of 0.70. This centralization of multi-disciplinary efficiency poses a strategic vulnerability, as the team's aggregate performance metric demonstrably declines when such pivotal contributors are unavailable.

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This research makes two theoretical contributions. To begin with, it confirms the relevance of Data Envelopment Analysis to the assessment of cricket performance, a tool that was used in the past as more studies focused on economic efficiency and football analytics (as mentioned by Ruiz and Sirvent, 2020, and Guzman and Morrow, 2021). The paper shows that aggregate statistics like total runs or wickets can be misleading without normalising to the amount of resources used in those two disciplines, i.e. balls faced or overs bowled.

Second, the All-Rounder Index development provides a new quantitative model of measuring the multidisciplinary value of players, which is a gap in the methodological analysis found by Bhattacharjee and Saikia (2016) on composite models of performance in cricket. These contributions are an improvement in the sports analytics literature because they offer reproducible, context-sensitive measures that intersect descriptive statistics and predictive modelling.

Practically, the research indicates definite policy guidelines to the board of Bangladesh Cricket and the coaches. Since the efficiency of bowling showed a higher correlation to match win probability ($r = 0.71$) than batting efficiency ($r = 0.42$), the focus of talent identification and development resources should be on improving the specialisation and the mastery of spin variation in death overs.

The statistics reveal that, although batting averages are quite decent, strike rate lapses and global standards stand at around 85.00 and in Bangladesh, the mean is around 80.00, which is an area of concern and therefore deserves specific technical intervention. The training programmes ought to focus on power-hitting techniques to be applied by middle-order batters to enhance the Boundary Percentage index, which currently stands at 10.42% on average in the cohort. In addition, the team selection policies are supposed to attempt diversity of the all-rounder talent pool. The fact that it relies largely on one high-efficiency all-rounder violates the principles of robustness as described by Stevenson and Brewer (2017); one of the strategic priorities that needs to be developed to reduce systemic vulnerability should be the creation of a secondary all-rounder that will be able to reach the All-Rounder Index of more than 0.70.

There are various limitations that have been recognised in this study.

To start with, the use of aggregate career data at ESPNcricinfo Statsguru does not allow a detailed contextual analysis of balls (Guo et al., 2025). Such factors as the property of pitch, weather, and the exact opposition strength were included as controlled factors but not directly modelled as independent variables, which Scarf et al. (2019) identified as a limiting factor that can affect distributional results in studies on cricket performance. Second, the study included 57 players, which is quite sufficient regarding the scope of the study but is quite small in comparison to worldwide datasets, which may restrict the applicability of the obtained efficiency frontiers. Third, the efficiency weighting model, where average, strike rate, and consistency count 40, 35, and 25, respectively, was based on the consensus of the literature based on the model of Hughes and Bartlett (2002) and not on empirical maximisation; other weightings did not produce statistically significant changes in the rankings of different players, although sensitivity analyses indicated that such weightings were also robust.

variations.

Lastly, the analyzing of gender-based comparative efficiency is a vacant opportunity since the research was only limited to men's cricket.

To overcome such shortcomings in future research, ball-by-ball data ought to be used to build contextualized efficiency measurements, including pressure-weighted DEA models including match situation variables. Longitudinal studies have the potential to follow the trajectory of

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efficiency of particular players to determine their high-performance periods, which will help guide career management, according to Wright et al. (2020). Also, the broadening of this analysis model to other associate countries, such as Afghanistan, Ireland, or Zimbabwe, e.g., would allow the comparative benchmarking of the analysis of whether the bowling-led efficiency model is typical of Bangladesh in particular or if it is a general trend in the emerging cricket countries.

Lastly, incorporating psychological resilience measures with performance information may investigate the mental robustness variables proposed by Talukdar and Bhattacharjee (2025), which offer a more comprehensive view of the performance of cricket that goes beyond the facet of technical performance. The future research should also consider validating these efficiency models using real-time match situations as stipulated by O'Donoghue (2010) to improve their predictive value in the live decision-support systems that may be used by the coaching staff during matches to improve their efficiency models.

Conclusion

This paper confirms that the efficiency of bowling is the main factor which determines the success of Bangladesh in ODIs between 2016 and 2026 and the effect of batting performance indicators is continuously less predictive than it is.

The mentioned efficiency imbalance indicates a major reliance on spin-based bowling actions and reveals a weak adaptation of the batting strike rate compared with international standards. As a result, sustainable competitive evolution requires the requisite strategic shift to the introduction of death-overs batting skill and non-single-player dependence on high-efficiency all-rounder resources. This study demonstrates that data envelopment analysis has a role to play in the performance modelling of cricket by confirming its validity in resource allocation optimization by associate nations using evidence-based talent identification.

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Conflict of Interest

Authors declare no conflicts of interest.

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