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Performance evaluation of cricket players in Indian Premier League using DEA

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Abstract: This study applies a data envelopment analysis (DEA) framework to assess Indian Premier League (IPL) player efficiency through a service-management perspective, positioning each athlete as a performance unit, whose on-field output can be objectively evaluated. Using publicly available data from 2023 season, this research conducts a performance evaluation on 20 batters and 20 bowlers, incorporating role-specific performance metrics such as balls faced, runs conceded, runs scored, and wickets taken. Basic DEA models were applied separately for batters and bowlers to ensure appropriate performance comparisons. Results showed notable efficiency variations, with a small group of players operating on the efficiency frontier as benchmarks. For demonstration, one batter and one bowler were selected as 'clients', illustrating the model's ability to identify undervalued high performers. Overall, the findings highlight DEA's strength in service management decision-making, supporting recruitment, retention, and role optimisation strategies.

Keywords: data envelopment analysis; DEA; sports; cricket; efficiency; performance analysis.

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1 Introduction

The performance evaluation of players in modern cricket – particularly in the dynamic and commercially dominant Twenty20 (T20) format – has become a central concern for contemporary sports management, especially in the broader context of service management. In professional leagues such as the Indian Premier League (IPL), player performance directly affects team success, financial outcomes, brand value, and fan engagement. Since franchises operate as complex business entities, managers increasingly rely on analytical tools to optimise team composition, resource allocation, and strategic planning within this high-stakes service environment. Geng et al. (2025), provide an operations management perspective on the business of sports, discussing scheduling, ticket pricing, broadcasting, and analytics as operations management problems.

Player evaluation in professional cricket is not only a performance measurement exercise, but a core sports and service management decision process. Berri et al. (2022) conduct a study to assess the determinants of playing time with a focus on the effects of players' national origin. IPL franchises operate within a competitive marketplace involving player auctions, salary caps, return-on-investment expectations, and strategic roster design. Managers must allocate financial resources efficiently, identify undervalued players, justify retention decisions, and optimise team composition amid commercial pressures. By framing player performance through data envelopment analysis (DEA), our study provides a managerial tool that supports evidence-based recruitment, contract valuation, and performance optimisation. The approach strengthens decisions at the intersection of analytics, financial management, and team strategy – central domains of modern sports and service management.

This paper explores the use of DEA as a rigorous, quantitative framework for evaluating player efficiency in the IPL Season 16 (2023). DEA, a non-parametric method rooted in operations research, enables the comparison of multiple decision-making units (DMUs) – in this case, individual players – based on various inputs (e.g., balls faced,

matches played, and overs bowled) and outputs (e.g., runs scored, wickets taken, matches won). By identifying efficiency frontiers, DEA helps sports managers distinguish between high-performing and underperforming players relative to their peers.

The relevance of applying DEA in sports management lies in its ability to translate performance data into actionable insights. Chatzistamoulou et al. (2022), offer a two-stage DEA model under heterogeneity which includes salary cap, organisational gap, and catch-up in the performance of NBA teams. Whitt (1992, cited frequently in 2024–2026) offers a foundational analysis of efficiency in multi-server queues, frequently cited in more recent efficiency work. Vink and Koskela-Huotari (2022) examine service design for institutional efficiency in complex ecosystems. For IPL franchises, this approach can assist key managerial decisions, including player recruitment, retention, contract valuation, and match strategy. Moreover, the auction-based team structure in the IPL amplifies the need for objective, data-driven decision models to justify investments in player talent. This aligns with managerial goals of maximising return on investment, maintaining competitive balance, and leveraging player analytics for sustained success.

The goal of this paper is two-fold: to identify the most efficient players using DEA and to propose improvement strategies for inefficient players with Excel tools such as Solver and Goal Seek. By offering a quantitative framework for performance analysis, this research contributes valuable insights to sports management, strategic decision-making, and the expanding literature on DEA applications within professional service contexts.

2 Literature survey

2.1 Data envelopment analysis

DEA is a widely applied non-parametric mathematical programming approach used to evaluate the productive efficiency of DMUs with multiple inputs and outputs. Originating from the seminal work of Charnes et al. (1978), DEA integrates concepts from operations research, econometrics, and management science (Ferrier and Lovell, 1990). Wei (2001) further extended the methodology by introducing additional non-parametric statistical estimation methods. DEA identifies efficient DMUs and highlights those with improvement potential, making it an effective tool for performance evaluation and benchmarking (Cooper et al., 2004). Chen (2023) studies how learning and skill development impact operational efficiency at both worker and system levels. Arora and Arora (2025) offer an empirical study on inception, growth and efficiency of small finance banks in India.

Several surveys have documented the evolution and applications of DEA. Emrouznejad et al. (2008) classified DEA studies by year, journal, author, and keywords. White and Bordoloi (2014) reviewed DEA models for resource and cost allocation in service industries, while Paradi and Zhu (2013) examined 80 studies on bank branch efficiency. Liu et al. (2013) analysed DEA applications across five key sectors: healthcare, banking, agriculture, education, and transportation, noting strong growth in energy, environmental, and financial applications. Recent developments also point to the increasing adoption of network DEA models. Raju et al. (2023) focus on operational

efficiency comparison over time via Malmquist productivity indices for container terminals of major Indian ports and Sri Lankan ports using DEA.

The *DEA Handbook* (Cooper et al., 2004) explains that in an input-oriented model, efficiency is improved by proportionally reducing inputs, while an output-oriented model seeks proportional output increases. Model orientation influences the efficiency frontier and the extent of improvement required. Banker and Morey (1986) addressed the integration of non-discretionary inputs, while Bordoloi et al. (2018) demonstrated input-level adjustments to move a DMU toward the frontier. Guajardo (2018) applied DEA to assess US special district libraries using cost-related outputs, and chance-constrained DEA (Charnes and Cooper, 1963) has been used to model uncertainty in service processes.

In recent years, DEA has been applied across diverse sectors – including sports – to evaluate processes involving non-marketable inputs and outputs or where weighting is difficult to determine (Singh, 2011).

2.1.1 *DEA in sports*

DEA applications span multiple sports, including tennis, soccer, basketball, baseball, handball, cricket, and Formula One racing. Ruiz et al. (2013) assessed professional tennis players by aggregating Association of Tennis Professionals (ATP) statistics, enabling benchmarking of strengths and weaknesses. Haas (2003) applied DEA to Major League Soccer data using wage-related inputs and match performance outputs. Espitia-Escuer and García-Cebrián (2004) analysed Spanish First-Division soccer, revealing that the most efficient teams were not always league leaders – a finding aligned with the ‘Moneyball’ approach (Lewis, 2004).

Anderson and Sharp (1997) introduced the Composite Batter Index to refine baseball performance analysis. In Formula One, Gutiérrez and Lozano (2014) found constructors could achieve similar performance with reduced budgets. Gutiérrez and Ruiz (2013) applied DEA to Spanish handball, identifying efficiency benchmarks for players. Fizel and D’itri (1996) measured managerial efficiency in college basketball, revealing that winning percentage alone can misrepresent coaching performance. Moreno and Lozano (2014) employed network-DEA for NBA team efficiency.

Other notable applications of DEA have been documented across various domains of sport management and performance evaluation. For instance, Einolf (2004) examined payroll efficiency in the National Football League (NFL) and Major League Baseball (MLB), while Villa and Lozano (2019) assessed offensive and defensive strategy efficiency in European football. Several studies have also applied DEA to the Olympic Games, evaluating national performance using medal counts in relation to socioeconomic inputs (dos Santos, 2011; Wu et al., 2010; Lei, 2015). In addition, Zamboni-Ferraresi et al. (2017) analysed revenue distribution efficiency within the UEFA Champions League, Ghotnian et al. (2019) investigated the operational efficiency of sports federations. Kheyri et al. (2023) develop DEA benchmarking for service dealers, comparable to player performance frontiers in sports, from the service industry context. Liu and Tsai (2023) examines service quality and customer perceptions in ski tourism, in a sports related service context.

These studies demonstrate DEA’s adaptability to both individual and team sports, as well as financial and operational aspects of performance.

2.2 DEA in cricket

DEA has been applied extensively in cricket across formats, including Test, One Day International (ODI), and Twenty20 (T20). Paton and Cooke (2005) analysed county cricket attendance as an output in DEA models, showing that match format and scheduling significantly influence spectator turnout. Sacheti et al. (2016) found no significant advantage from winning the toss in T20 internationals.

Player valuation studies include Karnik (2010), who estimated hedonic price equations for IPL players, finding premiums for younger and domestic players. Chakraborty et al. (2015) proposed a combinatorial auction for optimal team selection. Petersen et al. (2009) quantified positional physical demands in T20 cricket, while Prakash and Verma (2022) introduced the Deep Player Performance Index.

DEA-based player and team evaluation has been explored through several methodological innovations across the cricket analytics literature. Chaudhary et al. (2019) combined DEA with neural networks to create a hybrid framework capable of capturing nonlinear performance patterns, while Amin and Sharma (2014) used DEA to support player selection decisions specifically for IPL Season 4. Singh (2011) examined team efficiency in the 2009 IPL season by incorporating wage bills alongside on-field performance indicators, highlighting financial–performance trade-offs. Santhosh et al. (2023) adopted multi-criteria decision-making (MCDM) techniques to rank IPL teams using a broader set of qualitative and quantitative factors. Ravichandran et al. (2020) extended DEA into a graph-based framework for forecasting ‘Man of the Match’ outcomes. More recently, Garg and Bhardwaj (2023) and Chathurangi et al. (2025) refined integrated, role-specific evaluation metrics to better capture player specialisation within T20 cricket. This growing body of literature confirms DEA’s value in cricket analytics for identifying efficiency frontiers, benchmarking players, and supporting data-driven team selection and strategy. The above publications do not compare batters and bowlers explicitly using analytical tools. Our study applies DEA tool to IPL 2023 batters and bowlers to measure individual efficiency and identify performance benchmarks.

Other literature exists too for efficiency analysis using techniques other than DEA. Sahai et al. (2024) analyse how competency interventions, employee involvement, and change management practices affect effectiveness in IT industry in India. Pineda-Marin et al. (2024) apply efficiency analysis by assessing relative operational efficiency across high complexity hospitals of Bogota, Colombia.

3 Problem definition and data resource

In modern professional cricket, assessing players goes far beyond tallying runs or wickets. It functions as a strategic management activity that shapes how teams are built and sustained. Within leagues like the IPL, franchises compete in an environment defined by auctions, budget ceilings, commercial returns, and long-term squad planning. Decision-makers are therefore tasked with making smart financial choices – spotting hidden talent, defending contract renewals, and assembling balanced line-ups – while constantly navigating economic and market-driven constraints. With this motivation, we elaborate below, in a layered way, why we have selected the game of cricket, the format

of T20, the league of IPL, our choice of methodology namely DEA, and our source of data.

3.1 *Why cricket?*

Cricket originated in England during the mid-16th century (ESPN Sports Media Ltd., 2017) and expanded globally with the spread of the British Empire. Today, it is the second-most popular sport worldwide after football (World Atlas, Sports). Cricket is widely played across Asia, Africa, and Australia, with strong fan bases in England, Australia, and India. In recent years, its popularity has been gradually rising in the United States. Cricket is a team sport played between two sides of 11 players each and is contested at both international and domestic levels. The sport features three major formats: Test cricket (lasting up to five days), One-Day Internationals (50 overs per side), and the fast-paced Twenty20 (T20), which is the shortest and newest format.

3.2 *Why T20?*

Compared to Tests and One-Day Internationals, T20 cricket is a condensed and more engaging format. A typical T20 match lasts about three hours, with each team batting for 20 overs (120 balls), and each innings taking approximately 90 minutes. Its quick pace and high entertainment value make T20 appealing to a broad audience and align well with modern sports consumption habits.

3.3 *Why IPL?*

In India, cricket holds immense cultural and social significance. The IPL, launched in 2008, is a professional T20 league that has transformed the cricketing landscape. Mirroring leagues like the NFL and NBA, IPL has become a seasonal sporting spectacle. Its combination of glamour, short match durations, and top-tier talent has made it commercially lucrative and widely watched. Team owners bid for players through auctions, often offering higher compensation than traditional formats, which attracts elite international players. Governed by the Board of Control for Cricket in India (BCCI), IPL features eight regional teams playing in a round-robin format, followed by playoffs. The structure encourages competitiveness and ensures high entertainment value.

3.4 *Why DEA?*

DEA is a non-parametric method used to evaluate the efficiency of entities based on multiple inputs and outputs. In the context of IPL, DEA helps assess player performance objectively, eliminating personal bias from the selection process. It enables franchises to optimise team composition by quantifying the contributions of individual players in a balanced way. DEA has been widely used in sports analytics (Banker et al., 1984; Charnes et al., 1978) and is particularly useful where production functions are unknown. By comparing performance against an efficiency frontier, DEA helps identify both high-performing players and areas of improvement.

3.5 Why this data source?

The choice of data source is crucial for any analysis. For this study, data was collected from the official IPL T20 website, ensuring authenticity and reliability. The dataset from the 2023 season (Season 16) includes comprehensive batting and bowling statistics. For batters, inputs include balls faced and innings played; outputs consist of runs scored, matches won, and fifties scored. For bowlers, inputs are balls bowled and runs conceded; outputs include wickets taken, dot balls bowled, and matches won. In DEA modelling, optimal performance is characterised by minimising inputs while maximising outputs. This dataset enables a robust analysis of player efficiency, informing better selection and performance evaluation.

4 Model formulation

DEA is a strong choice for evaluating cricket players performance because it aligns naturally with the game's multi-dimensional nature. Conceptually, DEA treats each player as a DMU, comparing how effectively they convert multiple inputs (balls faced, overs bowled, resources used) into multiple outputs (runs, wickets, strike rate, bowling economy). Mathematically, DEA is non-parametric and does not require predefined weights or functional forms, allowing performance to emerge endogenously from the data. As a framework, it supports relative efficiency benchmarking, identifies best-practice players, and accommodates heterogeneity across roles (batters, bowlers, and all-rounders) in a unified, transparent manner.

For DEA analysis, we started by identifying relevant variables from the IPL 2023 dataset which are useful in efficiency analysis. For T20 style of cricket, we identified the following list of variables, separately for batting and bowling. After making the comprehensive batting and bowling list of variables, we categorised the selected variables into inputs and outputs.

The selected variables for batting are:

- batting style (right or left-handed)
- position in the batting order
- number of matches played
- number of matches won
- runs scored
- balls faced
- not-outs (not dismissed by the end of an innings)
- duck-outs (out on zero runs)
- 50's and 100's (runs)
- type of player (all-rounder or pure batter)
- physical attributes (height, weight, age, etc.).

The selected variables for bowling are:

- bowling style (right or left-handed)
- number of matches played
- number of matches won
- bowling speed
- balls bowled
- wickets taken
- economy rate
- runs conceded
- wide and no-balls,
- type of player (all-rounder or pure bowler)
- physical attributes (height, weight, age, etc.).

We researched a range of sources to obtain the necessary data for the analysis. Based on availability and relevance, we selected a subset from the broader dataset that best suited the objectives of our DEA framework. The process for determining the most appropriate input and output variables is described below.

Data were sourced from the official IPL website, focusing on the top 20 batters, ranked by total runs scored, and the top 20 bowlers, ranked by total wickets taken during the 2023 season. Data collection began only after the conclusion of the IPL 2023 season, ensuring that complete and consistent performance statistics were available for all selected players. This approach enabled a full-season perspective, which is essential for a robust and meaningful evaluation.

Following the initial data extraction, we examined multiple variables to assess their relevance for evaluating the performance of individual players. The selected attributes were then organised into two separate categories – inputs and outputs – tailored specifically for batting and bowling. This categorisation ensured that performance evaluation accounted for the distinct roles and skill sets associated with each discipline.

The variables selected for batting analysis are:

- a Inputs:
 - number of innings played
 - number of balls faced.
- b Outputs:
 - total runs scored
 - number of matches won
 - the number of times 50 or more runs scored per match.

The variables selected for bowling analysis are:

- a Inputs:
 - number of balls bowled
 - number of runs conceded.

b Outputs:

- total wickets taken
- number of matches won
- number of dot balls bowled.

In DEA analysis, a DMU is more likely to be on the efficient frontier by having a niche combination of inputs and outputs. We can achieve higher efficiency with smaller values of inputs and higher values of outputs.

For our analysis, we collected data for the above inputs and outputs for both batting and bowling from the IPL website. Those are listed in Tables 1 and 2.

Table 1 Basic batting data (top 20 batters) – inputs and outputs (see online version for colours)

<i>Batting data</i>					
<i>Batsman</i>	<i>Outputs</i>			<i>Inputs</i>	
	<i>Runs</i>	<i>Matches won</i>	<i>>50 runs per match</i>	<i>Balls faced</i>	<i>Innings played</i>
Shubman Gill	890	11	7	564	17
Faf du Plessis	730	7	8	475	14
Devon Conway	672	10	6	481	15
Virat Kohli	639	7	8	457	14
Yashasvi Jaiswal	625	7	6	382	14
Suryakumar Yadav	605	9	6	334	16
Ruturaj Gaikwad	590	10	4	400	15
David Warner	516	5	6	392	14
Rinku Singh	474	6	4	317	14
Ishan Kishan	454	9	3	318	15
Cameron Green	452	9	3	282	16
Heinrich Klaasen	448	3	3	253	11
Shivam Dube	418	9	3	264	14
Nitish Rana	413	6	3	293	14
Marcus Stoinis	408	8	3	272	15
Venkatesh Iyer	404	6	3	277	14
Glenn Maxwell	400	7	5	218	14
Jos Buttler	392	7	4	282	14
Kyle Mayers	379	7	4	263	13
Shikhar Dhawan	373	4	3	261	11

Once we finalised the inputs and outputs for batters and bowlers, we created an Excel spreadsheet to tabulate that dataset to apply our DEA model, with two inputs and three outputs, for each batting and bowling. The general DEA model is shown as follows,

$$\text{Maximise } E_i = u_1 O_{1i} + u_2 O_{2i}$$

Subject to:

$$\begin{aligned} v_1 I_{1i} + v_2 I_{2i} &= 1 \\ u_1 O_{1i} + u_2 O_{2i} - v_1 I_{1i} + v_2 I_{2i} &\leq 0 \quad \forall i = 1, 2, \dots, N \end{aligned}$$

where

- E_i = efficiency score for player i
- O_{1i} = first output for player i
- O_{2i} = second output for player i
- I_{1i} = first input for player i
- I_{2i} = second input for player i
- u_j and v_k are the coefficients for outputs and inputs respectively
- $u_j \geq 0$ for $j = 1$ and 2 , and $v_k \geq 0$ for $k = 1$ and 2 .

Table 2 Basic bowling data (top 20 bowlers) – inputs and outputs

<i>Bowler</i>	<i>Bowling data</i>				
	<i>Outputs</i>			<i>Inputs</i>	
	<i>Wickets</i>	<i>Matches won</i>	<i>Dot balls</i>	<i>Balls bowled</i>	<i>Runs conceded</i>
Mohammad Shami	28	11	193	390	522
Mohit Sharma	27	9	87	265	361
Rashid Khan	27	11	134	402	552
Piyush Chawla	22	9	121	366	495
Yuzvendra Chahal	21	7	97	317	432
Tushar Deshpande	21	10	137	341	564
Ravindra Jadeja	20	10	107	342	431
Varun Chakravarthy	20	6	124	316	429
Mohammad Siraj	19	7	161	312	376
Matheesha Pathirana	19	8	104	278	371
Arshdeep Singh	17	6	114	305	493
Ravi Bishnoi	16	8	97	303	391
Noor Ahmad	16	8	103	283	369
Bhuvneshwar Kumar	16	4	128	306	425
Ravichandran Ashwin	14	6	90	294	368
Akash Madhwal	14	5	53	153	219
Jason Behrendorff	14	6	92	252	387
Harshal Patel	14	6	87	282	454
Trent Boult	13	5	107	228	312
Deepak Chahar	13	5	82	204	297

The DEA model comprises outputs, inputs, and their corresponding coefficients. The values of these coefficients play a vital role in determining the efficiency of each player.

The DEA result identifies an efficiency frontier with DMU's that are 100% efficient. The non-efficient DMU's are assigned an efficiency score of less than 100%.

5 Results and discussion

After structuring the dataset appropriately in the spreadsheet, we conducted a DEA using Excel Solver to calculate the efficiency scores of batters and bowlers. Two separate spreadsheets were used for this purpose – for batting and bowling. Players who achieved an efficiency score of 100% represent the efficiency frontier. Table 3 presents the Solver output for the batting dataset, outlining the key results of our analysis.

Table 3 Batting model – solver result and client selection and comparison with efficient players (see online version for colours)

<i>Batting data</i>						
<i>Batsman</i>	<i>Outputs</i>			<i>Inputs</i>		<i>Efficiency</i>
	<i>Runs</i>	<i>Matches won</i>	<i>>50 runs per match</i>	<i>Balls faced</i>	<i>Innings played</i>	
Shubman Gill	890	11	7	564	17	100.00%
Faf du Plessis	730	7	8	475	14	85.09%
Devon Conway	672	10	6	481	15	97.60%
Virat Kohli	639	7	8	457	14	81.59%
Yashasvi Jaiswal	625	7	6	382	14	86.35%
Suryakumar Yadav	605	9	6	334	16	95.09%
Ruturaj Gaikwad	590	10	4	400	15	100.00%
David Warner	516	5	6	392	14	65.01%
Rinku Singh	474	6	4	317	14	74.95%
Ishan Kishan	454	9	3	318	15	92.38%
Cameron Green	452	9	3	282	16	90.97%
Heinrich Klaasen	448	9	3	253	11	63.46%
Shivam Dube	418	9	3	264	14	100.00%
Nitish Rana	413	6	3	293	14	72.99%
Marcus Stoinis	408	8	3	272	15	85.99%
Venkatesh Iyer	404	6	3	277	14	73.60%
Glenn Maxwell	400	7	4	282	14	86.54%
Jos Buttler	392	7	4	282	14	80.52%
Kyle Mayers	379	7	4	263	13	85.75%
Shikhar Dhawan	373	4	3	261	11	66.96%
	0.000570	0.073913		0.000916	0.047239	0.92
	1.00					

The DEA results revealed the current efficiency frontier among the set of DMUs. Out of 20 DMUs evaluated, three batters – Shubman Gill, Shivam Dube, and Ruturaj Gaikwad – achieved full efficiency, scoring 100%. These players constitute the efficiency frontier.

The remaining batters, who scored below 100%, are considered inefficient relative to the best-performing peers within the current dataset.

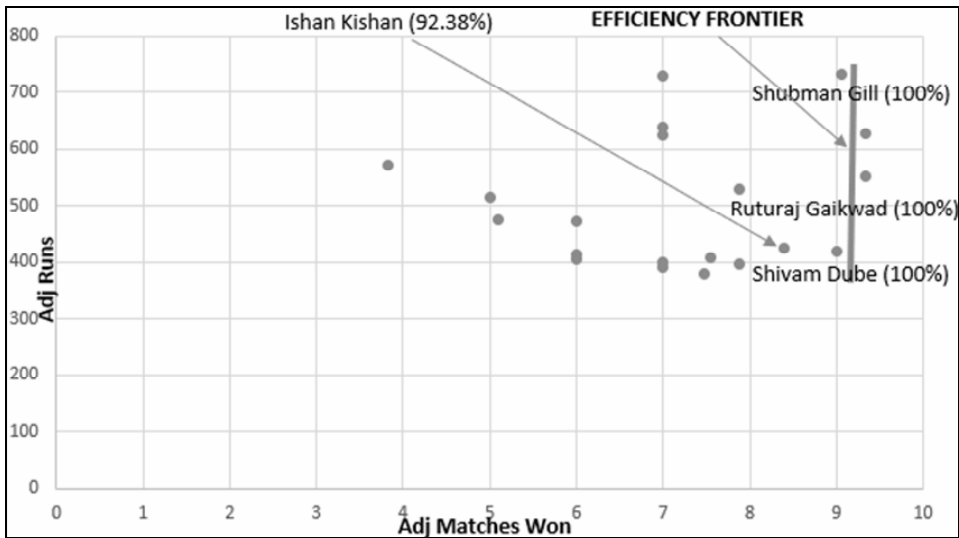
To provide practical relevance to our study, we selected Ishan Kishan as the focus of our improvement analysis. As a young player with significant potential, Kishan's current efficiency stands at 92.38%. The objective of our extended analysis is to explore various DEA methodologies that can help identify performance improvements necessary for Ishan Kishan to reach the efficiency frontier.

To better visualise the efficiency frontier, we plotted the normalised data in a two-dimensional graph. Normalisation was necessary to bring input and output variables to a common scale without distorting their relationships. We constructed a normalised model with innings played as the output variable at a constant value of 14. The two input variables – matches won and total runs – were accordingly normalised against this output. Table 4 illustrates the adjusted input values after normalisation with respect to innings played.

Based on Table 4, we generated an efficiency graph that plots each player's performance across the two input variables. Figure 1 presents this visual representation. Each player's location on the graph and their proximity to the efficiency frontier reflect their DEA-calculated efficiency. The efficiency frontier is depicted as the line connecting the data points for Shubman Gill, Shivam Dube and Ruturaj Gaikwad, who all achieved 100% efficiency. The closer a player lies to this frontier, the higher their relative efficiency.

Table 4 Batting model – normalised with respect to innings (see online version for colours)

<i>Batsman</i>	<i>Normalised innings</i>	<i>Match won</i>	<i>Adj. runs</i>
Shubman Gill	14	9.06	732.94
Faf du Plessis	14	7.00	730.00
Devon Conway	14	9.33	627.20
Virat Kohli	14	7.00	639.00
Yashasvi Jaiswal	14	7.00	625.00
Suryakumar Yadav	14	7.88	529.38
Ruturaj Gaikwad	14	9.33	550.67
David Warner	14	5.00	516.00
Rinku Singh	14	6.00	474.00
Ishan Kishan	14	8.40	423.73
Cameron Green	14	7.88	395.50
Heinrich Klaasen	14	3.82	570.18
Shivam Dube	14	9.00	418.00
Nitish Rana	14	6.00	413.00
Marcus Stoinis	14	7.47	380.80
Venkatesh Iyer	14	6.00	404.00
Glenn Maxwell	14	7.00	400.00
Jos Buttler	14	7.00	392.00
Kyle Mayers	14	7.54	408.15
Shikhar Dhawan	14	5.09	474.73

Figure 1 Batting model – efficiency frontier, client Ishan Kishan pointed

It is important to note that the three most efficient batters – Gill, Dube and Gaikwad – are not necessarily the highest scorers or the ones who played the fewest innings or faced the fewest balls. DEA uniquely evaluates efficiency by examining the ratio of weighted inputs to outputs, in this case using two input and three output variables. The analysis thus offers valuable insights for improving underperforming players. In the context of our client, Ishan Kishan, this approach provides a data-driven path to identify and implement performance enhancements aimed at reaching the efficiency frontier.

By this analysis, our DEA-based framework has successfully identified key performance benchmarks among batters, highlighting both strengths and areas for development. By leveraging this analysis, we can support players like Ishan Kishan in making targeted improvements to reach optimal efficiency. This methodology holds potential for broader applications across player development and strategic team planning.

We conducted a similar DEA-based analysis for bowling by using multiple input and output variables. The DEA results are presented in Table 5. Three of the 20 bowlers – Shami, Mohit and Chahar – achieved 100% efficiency. Interestingly, these players did not lead in any single metric such as wickets taken, matches won, dot balls bowled, or minimum runs or balls conceded. Their high efficiency scores indicate that their overall output-to-input ratios are superior when compared to other DMUs. As with the batting analysis, we selected a client for deeper evaluation – Piyush Chawla – who currently stands at an efficiency score of 79.35%.

As mentioned earlier, in the batting analysis, we used a normalised model with one output (innings) set to a constant value of 14, and two input variables: matches won and total runs. For the bowling analysis, we developed a normalised model featuring two outputs – wickets and dot balls – and one input: runs conceded. As shown in Table 6, the input value for runs conceded was fixed at 350 runs. Using these normalised values, we plotted a two-dimensional graph to visualise the efficiency frontier, illustrated in Figure 2.

Table 5 Bowling model – solver result and client selection and comparison with efficient players (see online version for colours)

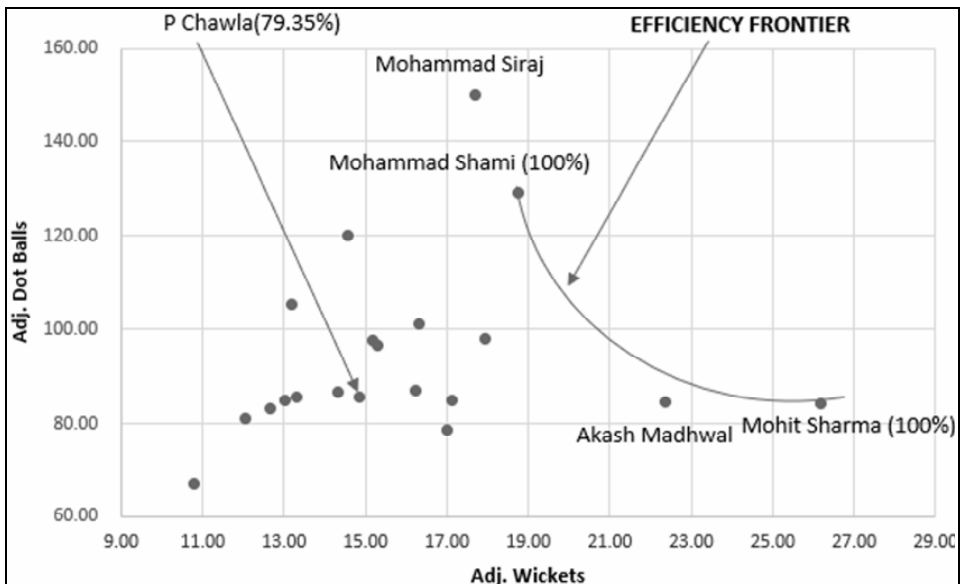
Bowling data						
Bowler	Outputs			Inputs		Efficiency
	Wickets	Matches won	Dot balls	Balls bowled	Runs conceded	
Mohammad Shami	28	11	193	390	522	100.00%
Mohit Sharma	27	9	87	265	361	100.00%
Rashid Khan	27	11	134	402	552	84.77%
Piyush Chawla	21	9	121	366	495	79.35%
Yuzvendra Chahal	21	7	97	317	432	71.43%
Tushar Deshpande	21	10	137	341	564	79.84%
Ravindra Jadeja	20	10	107	342	431	94.28%
Varun Chakravarthy	20	6	124	316	429	70.63%
Mohammad Siraj	19	7	161	312	376	96.44%
Matteesha Pathirana	19	8	104	278	371	93.03%
Arshdeep Singh	17	6	114	305	493	60.90%
Ravi Bishnoi	16	8	97	303	391	86.17%
Noor Ahmad	16	8	103	283	369	92.97%
Bhuvneshwar Kumar	16	4	128	306	425	57.81%
Ravichandran Ashwin	14	6	90	294	368	72.74%
Akash Madhwal	14	5	53	153	219	94.23%
Jason Behrendorff	14	6	92	252	387	71.63%
Harshal Patel	14	6	87	282	454	60.35%
Trent Boult	13	5	107	228	312	82.14%
Deepak Chahar	13	7	82	204	297	100.00%
		0.062478	0.001911	0.000381	0.001738	0.79
1.00						

Interestingly, this model produced a different DEA solution from the one reflected in Table 5. The updated solution identifies only two DMUs – Shami and Mohit – as lying on the efficiency frontier. The frontier itself is formed by the curve connecting these two data points. The relative inefficiency of all remaining bowlers is indicated by their respective distances from this curve.

This analysis highlights how DEA can reveal nuanced insights into player performance beyond surface-level statistics. The bowling efficiency frontier, like the batting counterpart, underscores that optimal efficiency is not solely dependent on isolated achievements but on balanced performance across multiple variables. By identifying Piyush Chawla's position relative to this frontier, we can now explore targeted strategies to enhance his efficiency, supporting data-driven decisions in team management and player development.

Table 6 Bowling model – normalised with respect to runs conceded

<i>Bowlers</i>	<i>Normalized wickets</i>	<i>Adj. balls</i>	<i>Adj. runs con</i>
Mohammad Shami	20.00	278.57	372.86
Mohit Sharma	20	196.30	267.41
Rashid Khan	20.00	297.78	408.89
Piyush Chawla	20.00	348.57	471.43
Yuzvendra Chahal	20.00	301.90	411.43
Tushar Deshpande	20.00	324.76	537.14
Ravindra Jadeja	20.00	342.00	431.00
Varun Chakravarthy	20.00	316.00	429.00
Mohammad Siraj	20.00	328.42	395.79
Matteesha Pathirana	20.00	292.63	390.53
Arshdeep Singh	20.00	358.82	580.00
Ravi Bishnoi	20.00	378.75	488.75
Noor Ahmad	20.00	353.75	461.25
Bhuvneshwar Kumar	20.00	382.50	531.25
Ravichandran Ashwin	20.00	420.00	525.71
Akash Madhwal	20.00	218.57	312.86
Jason Behrendorff	20.00	360.00	552.86
Harshal Patel	20.00	402.86	648.57
Trent Boult	20.00	350.77	480.00
Deepak Chahar	20.00	313.85	456.92

Figure 2 Bowling model – efficiency frontier, client Piyush Chawla pointed

Therefore, DEA is a very helpful tool in dealing with multiple variable situations. Next, we will take a deeper dive into our results for further analysis and managerial implications. We will do this separately for batting and bowling, one at a time.

The DEA results generated using Excel Solver provide a clear, data-driven assessment of relative efficiency among cricket players, identifying both best-practice performers and those operating below the efficiency frontier. These findings move beyond traditional statistics by revealing how effectively players convert opportunities into outcomes. However, efficiency scores alone do not create improvement; they serve as a diagnostic starting point. The next phase of analysis builds on these results to extract actionable managerial insights. By examining performance gaps, peer benchmarks, and target projections, we can develop strategic recommendations aimed at enhancing individual player performance and optimising overall team effectiveness.

6 Analysis and managerial implications

6.1 Batting: analysis and managerial implications

6.1.1 Batting: analysis

From our DEA analysis, the objective is to elevate our client, Ishan Kishan, from his current efficiency score of 92.38% to 100%. We considered five variables to determine each batter's efficiency. To explore improvement strategies, we employed Excel's 'Goal Seek' to adjust one variable at a time while keeping the other variables constant. This allowed us to derive an initial solution. We then used Excel's 'Solver' feature to refine these adjustments and validate the optimal value for each scenario.

Table 7a Batting model – initial goal seek results on output 2 (matches won)
(see online version for colours)

<i>Batting data</i>						
<i>Batsman</i>	<i>Outputs</i>			<i>Inputs</i>		<i>Efficiency</i>
	<i>Runs</i>	<i>Matches won</i>	<i>>50 runs per match</i>	<i>Balls faced</i>	<i>Innings played</i>	
Shubman Gill	890	11	7	564	17	100.00%
Faf du Plessis	730	7	8	475	14	85.09%
Devon Conway	672	10	6	481	15	97.60%
Virat Kohli	639	7	8	457	14	81.59%
Yashasvi Jaiswal	625	7	6	382	14	86.35%
Suryakumar Yadav	605	9	6	334	16	95.09%
Ruturaj Gaikwad	590	10	4	400	15	100.00%
David Warner	516	5	6	392	14	65.01%
Rinku Singh	474	6	4	317	14	74.95%
Ishan Kishan	454	10.03	3	318	15	100.00%
Cameron Green	452	9	3	282	16	90.97%
Heinrich Klaasen	448	3	3	253	11	63.46%
Shivam Dube	418	9	3	264	14	100.00%

Table 7a Batting model – initial goal seek results on output 2 (matches won) (continued)
(see online version for colours)

<i>Batting data</i>						
<i>Batsman</i>	<i>Outputs</i>			<i>Inputs</i>		<i>Efficiency</i>
	<i>Runs</i>	<i>Matches won</i>	<i>>50 runs per match</i>	<i>Balls faced</i>	<i>Innings played</i>	
Nitish Rana	413	6	3	293	14	72.99%
Marcus Stoinis	408	8	3	272	15	85.99%
Venkatesh Iyer	404	6	3	277	14	73.60%
Gleen Maxwell	400	7	5	218	14	86.54%
Jos Buttler	392	7	4	282	14	80.52%
Kyle Mayers	379	7	4	263	13	85.75%
Shikhar Dhawan	373	4	3	261	11	66.96%
	0.000570	0.073913	-	0.000916	0.047239	1.00
	1.00					

Table 7b Batting model – final DEA results using solver on output 2 (see online version for colours)

<i>Batting data</i>						
<i>Batsman</i>	<i>Outputs</i>			<i>Inputs</i>		<i>Efficiency</i>
	<i>Runs</i>	<i>Matches won</i>	<i>>50 runs per match</i>	<i>Balls faced</i>	<i>Innings played</i>	
Shubman Gill	890	11	7	564	17	100.00%
Faf du Plessis	730	7	8	475	14	85.09%
Devon Conway	672	10	6	481	15	97.60%
Virat Kohli	639	7	8	457	14	81.59%
Yashasvi Jaiswal	625	7	6	382	14	86.35%
Suryakumar Yadav	605	9	6	334	16	95.09%
Ruturaj Gaikwad	590	10	4	400	15	100.00%
David Warner	516	5	6	392	14	65.01%
Rinku Singh	474	6	4	317	14	74.95%
Ishan Kishan	454	10.03	3	318	15	100.00%
Cameron Green	452	9	3	282	16	90.97%
Heinrich Klaasen	448	3	3	253	11	63.46%
Shivam Dube	418	9	3	264	14	100.00%
Nitish Rana	413	6	3	293	14	72.99%
Marcus Stoinis	408	8	3	272	15	85.99%
Venkatesh Iyer	404	6	3	277	14	73.60%
Gleen Maxwell	400	7	5	218	14	86.54%
Jos Buttler	392	7	4	282	14	80.52%
Kyle Mayers	379	7	4	263	13	85.75%
Shikhar Dhawan	373	4	3	261	11	66.96%
	0.000570	0.073913	-	0.000916	0.047239	1.00
	1.00					

First, we examined output 2 – number of matches won – as the adjustable variable. Using Goal Seek, we set the desired efficiency to 100% and determined that Kishan's team would need to win 10.03 matches for him to become fully efficient. This scenario is detailed in Table 7a.

While Goal Seek adjusts only Kishan's efficiency to 100%, we needed to understand how this adjustment affects the efficiencies of rest of the batters. To do this, we re-ran the Solver across all DMUs. Interestingly, the efficiency scores of other players remained unchanged. The updated output from this analysis is shown in Table 7b.

Next, we adjusted output 1 – runs scored – while keeping the remaining attributes constant. Goal Seek revealed that Kishan would need to score 588 runs during the IPL season to attain 100% efficiency. Table 8a outlines these results.

Table 8a Batting model – initial goal seek results on output 1 (runs) (see online version for colours)

<i>Batting data</i>						
<i>Batsman</i>	<i>Outputs</i>			<i>Inputs</i>		<i>Efficiency</i>
	<i>Runs</i>	<i>Matches won</i>	<i>>50 runs per match</i>	<i>Balls faced</i>	<i>Innings played</i>	
Shubman Gill	890	11	7	564	17	100.00%
Faf du Plessis	730	7	8	475	14	85.09%
Devon Conway	672	10	6	481	15	97.60%
Virat Kohli	639	7	8	457	14	81.59%
Yashasvi Jaiswal	625	7	6	382	14	86.35%
Suryakumar Yadav	605	9	6	334	16	95.09%
Ruturaj Gaikwad	590	10	4	400	15	100.00%
David Warner	516	5	6	392	14	65.01%
Rinku Singh	474	6	4	317	14	74.95%
Ishan Kishan	588	9	3	318	15	100.00%
Cameron Green	452	9	3	282	16	90.97%
Heinrich Klaasen	448	3	3	253	11	63.46%
Shivam Dube	418	9	3	264	14	100.00%
Nitish Rana	413	6	3	293	14	72.99%
Marcus Stoinis	408	8	3	272	15	85.99%
Venkatesh Iyer	404	6	3	277	14	73.60%
Gleen Maxwell	400	7	5	218	14	86.54%
Jos Buttler	392	7	4	282	14	80.52%
Kyle Mayers	379	7	4	263	13	85.75%
Shikhar Dhawan	373	4	3	261	11	66.96%
	0.000570	0.073913	-	0.000916	0.047239	1.00
	1.00					

Table 8b Batting model – final DEA results using solver on output 1 (runs) (see online version for colours)

<i>Batting data</i>						
<i>Batsman</i>	<i>Outputs</i>			<i>Inputs</i>		<i>Efficiency</i>
	<i>Runs</i>	<i>Matches won</i>	<i>>50 runs per match</i>	<i>Balls faced</i>	<i>Innings played</i>	
Shubman Gill	890	11	7	564	17	100.00%
Faf du Plessis	730	7	8	475	14	85.09%
Devon Conway	672	10	6	481	15	97.60%
Virat Kohli	639	7	8			
457	14	81.59%				
Yashasvi Jaiswal	625	7	6	382	14	86.35%
Suryakumar Yadav	605	9	6	334	16	95.09%
Ruturaj Gaikwad	590	10	4	400	15	100.00%
David Warner	516	5	6	392	14	65.01%
Rinku Singh	474	6	4	317	14	74.95%
Ishan Kishan	454	10.03	3	318	15	100.00%
Cameron Green	452	9	3	282	16	90.97%
Heinrich Klaasen	448	3	3	253	11	63.46%
Shivam Dube	418	9	3	264	14	100.00%
Nitish Rana	413	6	3	293	14	72.99%
Marcus Stoinis	408	8	3	272	15	85.99%
Venkatesh Iyer	404	6	3	277	14	73.60%
Gleen Maxwell	400	7	5	218	14	86.54%
Jos Buttler	392	7	4	282	14	80.52%
Kyle Mayers	379	7	4	263	13	85.75%
Shikhar Dhawan	373	4	3	261	11	66.96%
	0.001701	-	-	0.003145	-	1.00
	1.00					

Following the same procedure, we used Solver to evaluate the system-wide effect of this change. Unlike the previous variable, adjusting runs did impact the efficiency of other players. As illustrated in Table 8b, the efficiency frontier shifted, placing Ishan Kishan on the frontier in place of Shubman Gill. This underscores the dynamic nature of DEA, where changing one player's efficiency can alter the benchmark set of efficient DMUs.

We then explored input 1 – balls faced – as the variable of interest. The analysis showed that Kishan would need to reduce the number of balls faced to 235, down from 318, to be deemed fully efficient. The Goal Seek output is presented in Table 9a.

Re-running Solver after this adjustment again led to changes in the frontier. Table 9b indicates that Kishan joins the efficiency frontier, replacing one of the earlier efficient players. This reaffirms that the efficiency frontier evolves when the performance of a single DMU is enhanced, highlighting the interdependent nature of DEA.

Table 9a Batting model – initial goal seek results on input 1 (balls faced) (see online version for colours)

<i>Batting data</i>						
<i>Batsman</i>	<i>Outputs</i>			<i>Inputs</i>		<i>Efficiency</i>
	<i>Runs</i>	<i>Matches won</i>	<i>>50 runs per match</i>	<i>Balls faced</i>	<i>Innings played</i>	
Shubman Gill	890	11	7	564	17	100.00%
Faf du Plessis	730	7	8	475	14	85.09%
Devon Conway	672	10	6	481	15	97.60%
Virat Kohli	639	7	8	457	14	81.59%
Yashasvi Jaiswal	625	7	6	382	14	86.35%
Suryakumar Yadav	605	9	6	334	16	95.09%
Ruturaj Gaikwad	590	10	4	400	15	100.00%
David Warner	516	5	6	392	14	65.01%
Rinku Singh	474	6	4	317	14	74.95%
Ishan Kishan	454	9	3	235	15	100.00%
Cameron Green	452	9	3	282	16	90.97%
Heinrich Klaasen	448	3	3	253	11	63.46%
Shivam Dube	418	9	3	264	14	100.00%
Nitish Rana	413	6	3	293	14	72.99%
Marcus Stoinis	408	8	3	272	15	85.99%
Venkatesh Iyer	404	6	3	277	14	73.60%
Gleen Maxwell	400	7	5	218	14	86.54%
Jos Buttler	392	7	4	282	14	80.52%
Kyle Mayers	379	7	4	263	13	85.75%
Shikhar Dhawan	373	4	3	261	11	66.96%
	0.000570	0.073913	-	0.000916	0.047239	0.92
	0.92					

Table 9b Batting model – final DEA results using solver on input 1 (balls) (see online version for colours)

<i>Batting data</i>						
<i>Batsman</i>	<i>Outputs</i>			<i>Inputs</i>		<i>Efficiency</i>
	<i>Runs</i>	<i>Matches won</i>	<i>>50 runs per match</i>	<i>Balls faced</i>	<i>Innings played</i>	
Shubman Gill	890	11	7	564	17	81.61%
Faf du Plessis	730	7	8	475	14	79.48%
Devon Conway	672	10	6	481	15	72.25%
Virat Kohli	639	7	8	457	14	72.31%
Yashasvi Jaiswal	625	7	6	382	14	84.62%
Suryakumar Yadav	605	9	6	334	16	93.68%

Table 9b Batting model – final DEA results using solver on input 1 (balls) (continued)
(see online version for colours)

<i>Batting data</i>						
<i>Batsman</i>	<i>Outputs</i>			<i>Inputs</i>		<i>Efficiency</i>
	<i>Runs</i>	<i>Matches won</i>	<i>>50 runs per match</i>	<i>Balls faced</i>	<i>Innings played</i>	
Ruturaj Gaikwad	590	10	4	400	15	76.28%
David Warner	516	5	6	392	14	68.08%
Rinku Singh	474	6	4	317	14	77.33%
Ishan Kishan	454	9	3	235	15	100.00%
Cameron Green	452	9	3	282	16	82.90%
Heinrich Klaasen	448	3	3	253	11	91.58%
Shivam Dube	418	9	3	264	14	81.89%
Nitish Rana	413	6	3	293	14	72.90%
Marcus Stoinis	408	8	3	272	15	77.58%
Venkatesh Iyer	404	6	3	277	14	75.43%
Gleen Maxwell	400	7	5	218	14	94.90%
Jos Buttler	392	7	4	282	14	71.89%
Kyle Mayers	379	7	4	263	13	74.53%
Shikhar Dhawan	373	4	3	261	11	73.91%
	0.002203	-	-	0.004259	-	1.00
	1.00					

Table 10a Batting model – initial goal seek results on input 2 (innings played)
(see online version for colours)

<i>Batting data</i>						
<i>Batsman</i>	<i>Outputs</i>			<i>Inputs</i>		<i>Efficiency</i>
	<i>Runs</i>	<i>Matches won</i>	<i>>50 runs per match</i>	<i>Balls faced</i>	<i>Innings played</i>	
Shubman Gill	890	11	7	564	17	100.00%
Faf du Plessis	730	7	8	475	14	85.09%
Devon Conway	672	10	6	481	15	97.60%
Virat Kohli	639	7	8	457	14	81.59%
Yashasvi Jaiswal	625	7	6	382	14	86.35%
Suryakumar Yadav	605	9	6	334	16	95.09%
Ruturaj Gaikwad	590	10	4	400	15	100.00%
David Warner	516	5	6	392	14	65.01%
Rinku Singh	474	6	4	317	14	74.95%
Ishan Kishan	454	9	3	318	13.39	99.99%
Cameron Green	452	9	3	282	16	90.97%
Heinrich Klaasen	448	3	3	253	11	63.46%
Shivam Dube	418	9	3	264	14	100.00%
Nitish Rana	413	6	3	293	14	72.99%

Table 10a Batting model – initial goal seek results on input 2 (innings played) (continued)
(see online version for colours)

<i>Batting data</i>						
<i>Batsman</i>	<i>Outputs</i>			<i>Inputs</i>		<i>Efficiency</i>
	<i>Runs</i>	<i>Matches won</i>	<i>>50 runs per match</i>	<i>Balls faced</i>	<i>Innings played</i>	
Marcus Stoinis	408	8	3	272	15	85.99%
Venkatesh Iyer	404	6	3	277	14	73.60%
Gleen Maxwell	400	7	5	218	14	86.54%
Jos Buttler	392	7	4	282	14	80.52%
Kyle Mayers	379	7	4	263	13	85.75%
Shikhar Dhawan	373	4	3	261	11	66.96%
	0.000570	0.073913	-	0.000916	0.047239	0.92
	0.92					

Table 10b Batting model – final DEA results using solver on input 2 (innings played)
(see online version for colours)

<i>Batting data</i>						
<i>Batsman</i>	<i>Outputs</i>			<i>Inputs</i>		<i>Efficiency</i>
	<i>Runs</i>	<i>Matches won</i>	<i>>50 runs per match</i>	<i>Balls faced</i>	<i>Innings played</i>	
Shubman Gill	890	11	7	564	17	99.97%
Faf du Plessis	730	7	8	475	14	85.02%
Devon Conway	672	10	6	481	15	97.60%
Virat Kohli	639	7	8	457	14	81.54%
Yashasvi Jaiswal	625	7	6	382	14	86.28%
Suryakumar Yadav	605	9	6	334	16	95.04%
Ruturaj Gaikwad	590	10	4	400	15	100.00%
David Warner	516	5	6	392	14	64.93%
Rinku Singh	474	6	4	317	14	74.89%
Ishan Kishan	454	9	3	318	13.39	100.00%
Cameron Green	452	9	3	282	16	90.95%
Heinrich Klaasen	448	3	3	253	11	63.32%
Shivam Dube	418	9	3	264	14	100.00%
Nitish Rana	413	6	3	293	14	72.94%
Marcus Stoinis	408	8	3	272	15	85.97%
Venkatesh Iyer	404	6	3	277	14	73.55%
Gleen Maxwell	400	7	5	218	14	86.49%
Jos Buttler	392	7	4	282	14	80.50%
Kyle Mayers	379	7	4	263	13	85.73%
Shikhar Dhawan	373	4	3	261	11	66.88%
	0.000613	0.080213	-	0.000988	0.051227	1.00
	1.00					

We followed a similar approach for input 2 – innings played. The model suggested Kishan would need to reduce his innings played to 13.39 from 15 to reach full efficiency. Table 10a presents this finding.

Subsequently, the Solver showed that this modification alters the frontier to include Ishan Kishan alongside Ruturaj Gaikwad and Shivam Dube. The updated results, shown in Table 10b, further demonstrate that efforts to optimise one player's efficiency may recalibrate the benchmark group entirely.

6.1.2 Batting: managerial implications

From Table 4, the DEA results show that four out of five variables have non-zero coefficients, indicating their relevance in the efficiency calculation. However, the output variable 'more than 50 runs per match' has a coefficient of zero, rendering it irrelevant in the current model. To ensure a comprehensive analysis of inefficient DMUs, all selected variables must contribute to the efficiency score – particularly output 1 (runs scored), which must be non-zero.

To address variable irrelevance, we applied sensitivity analysis. This technique allows managers to explore how adjustments to coefficient values influence the optimal solution. Once Solver determines an initial result, a sensitivity report can be generated to explore these possibilities.

Table 11 displays the sensitivity report for the batting analysis. Notably, the current value of output 3 (> 50 runs) is 3, with an allowable increase of 0.204. Increasing this variable beyond the allowable range, specifically to 3.21 or higher, would make output 3 relevant in the model. Table 12 confirms this, as it shows a non-zero coefficient for this output variable, meaning its contribution is now recognised in the efficiency score.

From the cumulative analysis, we conclude that Ishan Kishan can reach 100% efficiency either by increasing his team's match wins to 10.03 or by scoring 588 runs. These insights not only offer personalised guidance for player development but also emphasise the importance of individual contributions to team success. Based on the above analysis, the manager of the team that Ishan Kishan plays for, can scrutinise the current team structure and take policy level decisions on how to make Ishan Kishan as close to 100% efficient as possible. This analysis provides a robust framework for strategic decision-making in team and player management.

Table 11 Batting model – sensitivity report (see online version for colours)

Cell	Name	Final value	Objective coefficient	Allowable increase	Allowable decrease
Output 1	Runs	0.000569517	454	15.02753967	1.230769231
Output 2	Matches won	0.073912998	9	0.024464832	0.288358029
Output 3	>50 runs in match	0	3	0.204603771	1E+30
Input 1	Balls faced	0.000916405	0	9.659554513	1.161061947
Input 2	Innings played	0.047238876	0	0.054767073	0.455639364

This detailed DEA-based exploration demonstrates how incremental changes in a player's performance metrics can significantly impact both their individual efficiency and the overall efficiency frontier. Through tools like Goal Seek, Solver, and sensitivity analysis, we derived actionable strategies to optimise Ishan Kishan's performance.

Moreover, the study underscores the interconnectedness of players' performances in setting the efficiency benchmark. These insights are invaluable for coaches, analysts, and management teams seeking to make data-driven decisions that enhance both individual and team outcomes.

Table 12 Batting model – adding allowable increase to output 3 to make its corresponding coefficient relevant (see online version for colours)

<i>Batting data</i>							
<i>Batsman</i>	<i>Outputs</i>			<i>Inputs</i>		<i>Sum product</i>	<i>Efficiency</i>
	<i>Runs</i>	<i>Matches won</i>	<i>>50 runs per match</i>	<i>Balls faced</i>	<i>Innings played</i>		
Shubman Gill	890	11	7	564	17	-	100.00%
Faf du Plessis	730	7	8	475	14	(0.13863)	85.94%
Devon Conway	672	10	6	481	15	-	100.00%
Virat Kohli	639	7	8	457	14	(0.15222)	85.48%
Yashasvi Jaiswal	625	7	6	382	14	(0.13672)	86.25%
Suryakumar Yadav	605	9	6	334	16	(0.04728)	95.55%
Ruturaj Gaikwad	590	10	4	400	15	-	100.00%
David Warner	516	5	6	392	14	(0.33934)	66.12%
Rinku Singh	474	6	4	317	14	(0.25015)	73.61%
Ishan Kishan	454	9	3.2	318	15	(0.07630)	92.37%
Cameron Green	452	9	3	282	16	(0.10591)	89.67%
Heinrich Klaasen	448	3	3	253	11	(0.32011)	57.18%
Shivam Dube	418	9	3	264	14	-	100.00%
Nitish Rana	413	6	3	293	14	(0.26782)	71.22%
Marcus Stoinis	408	8	3	272	15	(0.14195)	85.32%
Venkatesh Iyer	404	6	3	277	14	(0.25896)	71.22%
Gleen Maxwell	400	7	5	218	14	(0.10165)	88.41%
Jos Buttler	392	7	4	282	14	(0.16706)	81.89%
Kyle Mayers	379	7	4	263	13	(0.10576)	87.67%
Shikhar Dhawan	373	4	3	261	11	(0.26585)	64.71%
	0.000291	0.081848	0.017132	0.000718	0.051447		0.92
	1.00						

6.2 Bowling: analysis and managerial implications

6.2.1 Bowling: analysis

We conducted a parallel DEA analysis for bowling, focusing on improving the efficiency of our client, Piyush Chawla, who currently holds a score of 79.35%. Our objective is to help him reach full efficiency. The DEA results, shown in Table 13, indicate that two out of the three outputs – wickets and dot balls – are relevant, while the sole relevant input is runs conceded.

Using Goal Seek, we adjusted the input variable ‘runs conceded’ while keeping all other attributes constant. The analysis revealed that Chawla would need to reduce his runs conceded from 495 to 376.19 to achieve 100% efficiency. This scenario is detailed in Table 13a.

Table 13a Bowling model – initial goal seek results on input 2 (runs conceded)
(see online version for colours)

Bowling data						
Bowler	Outputs			Inputs		Efficiency
	Wickets	Matches won	Dot balls	Balls bowled	Runs conceded	
Mohammad Shami	28	11	193	390	522	100.00%
Mohit Sharma	27	9	87	265	361	100.00%
Rashid Khan	27	11	134	402	552	84.77%
Piyush Chawla	21	9	121	366	376.19	100.00%
Yuzvendra Chahal	21	7	97	317	432	71.43%
Tushar Deshpande	21	10	137	341	564	79.84%
Ravindra Jadeja	20	10	107	342	431	94.28%
Varun Chakravarthy	20	6	124	316	429	70.63%
Mohammad Siraj	19	7	161	312	376	96.44%
Matteesha Pathirana	19	8	104	278	371	93.03%
Arshdeep Singh	17	6	114	305	493	60.90%
Ravi Bishnoi	16	8	97	303	391	86.17%
Noor Ahmad	16	8	103	283	369	92.97%
Bhuvneshwar Kumar	16	4	128	306	425	57.81%
Ravichandran Ashwin	14	6	90	294	368	72.74%
Akash Madhwal	14	5	53	153	219	94.23%
Jason Behrendorff	14	6	92	252	387	71.63%
Harshal Patel	14	6	87	282	454	60.35%
Trent Boult	13	5	107	228	312	82.14%
Deepak Chahar	13	7	82	204	297	100.00%
	-	0.062478	0.001911	0.000381	0.001738	0.79

Table 13b Bowling model – final DEA results using solver on input 2 (runs conceded)
(see online version for colours)

Bowling data						
Bowler	Outputs			Inputs		Efficiency
	Wickets	Matches won	Dot balls	Balls bowled	Runs conceded	
Mohammad Shami	28	11	193	390	522	99.24%
Mohit Sharma	27	9	87	265	361	100.00%
Rashid Khan	27	11	134	402	552	81.42%
Piyush Chawla	21	9	121	366	376.2	100.00%
Yuzvendra Chahal	21	7	97	317	432	72.46%
Tushar Deshpande	21	10	137	341	564	73.08%
Ravindra Jadeja	20	10	107	342	431	87.12%
Varun Chakravarthy	20	6	124	316	429	74.74%
Mohammad Siraj	19	7	161	312	376	100.00%
Matteesha Pathirana	19	8	104	278	371	89.41%
Arshdeep Singh	17	6	114	305	493	60.56%
Ravi Bishnoi	16	8	97	303	391	80.03%
Noor Ahmad	16	8	103	283	369	86.59%
Bhuvneshwar Kumar	16	4	128	306	425	64.34%
Ravichandran Ashwin	14	6	90	294	368	70.94%
Akash Madhwal	14	5	53	153	219	92.23%
Jason Behrendorff	14	6	92	252	387	68.03%
Harshal Patel	14	6	87	282	454	56.78%
Trent Boult	13	5	107	228	312	82.58%
Deepak Chahar	13	7	82	204	297	89.88%
	0.009830	0.062478	0.001911	0.000381	0.001738	1.0
	1.00					

Although Goal Seek forces Chawla's efficiency score to 100%, we needed to understand the broader impact on the overall efficiency landscape. By rerunning Solver, we observed a shift in the efficiency frontier, which now includes Chawla, Mohit Sharma, and Mohammad Siraj, replacing the original set of efficient bowlers. The updated outcomes are presented in Table 13b, demonstrating the dynamic nature of DEA when promoting a specific DMU to the frontier.

We then analysed output 2 – dot balls bowled – as the changing variable using Goal Seek. The results indicated that Chawla would require 121 dot balls instead of his original 229 to attain full efficiency. This analysis is illustrated in Table 14a.

Upon re-evaluating the model using Solver, we again found notable changes in the efficiency landscape. As shown in Table 14a, Chawla becomes the only player on the new efficiency frontier. This reinforces the idea that individual adjustments can significantly impact DEA outcomes and alter the benchmarking standards.

Table 14a Bowling model – initial goal seek results on output 3 (dot balls) (see online version for colours)

<i>Bowling data</i>						
<i>Bowler</i>	<i>Outputs</i>			<i>Inputs</i>		<i>Efficiency</i>
	<i>Wickets</i>	<i>Matches won</i>	<i>Dot balls</i>	<i>Balls bowled</i>	<i>Runs conceded</i>	
Mohammad Shami	28	11	193	390	522	100.00%
Mohit Sharma	27	9	87	265	361	100.00%
Rashid Khan	27	11	134	402	552	84.77%
Piyush Chawla	21	9	229	366	495	100.00%
Yuzvendra Chahal	21	7	97	317	432	71.43%
Tushar Deshpande	21	10	137	341	564	79.84%
Ravindra Jadeja	20	10	107	342	431	94.28%
Varun Chakravarthy	20	6	124	316	429	70.63%
Mohammad Siraj	19	7	161	312	376	96.44%
Matteesha Pathirana	19	8	104	278	371	93.03%
Arshdeep Singh	17	6	114	305	493	60.90%
Ravi Bishnoi	16	8	97	303	391	86.17%
Noor Ahmad	16	8	103	283	369	92.97%
Bhuvneshwar Kumar	16	4	128	306	425	57.81%
Ravichandran Ashwin	14	6	90	294	368	72.74%
Akash Madhwal	14	5	53	153	219	94.23%
Jason Behrendorff	14	6	92	252	387	71.63%
Harshal Patel	14	6	87	282	454	60.35%
Trent Boult	13	5	107	228	312	82.14%
Deepak Chahar	13	7	82	204	297	100.00%
-	-	0.062478	0.001911	0.000381	0.001738	1.00
1.00						

Table 14b Bowling model – final DEA results using solver on output 3 (dot balls) (see online version for colours)

<i>Bowling data</i>						
<i>Bowler</i>	<i>Outputs</i>			<i>Inputs</i>		<i>Efficiency</i>
	<i>Wickets</i>	<i>Matches won</i>	<i>Dot balls</i>	<i>Balls bowled</i>	<i>Runs conceded</i>	
Mohammad Shami	28	11	193	390	522	79.91%
Mohit Sharma	27	9	87	265	361	52.08%
Rashid Khan	27	11	134	402	552	52.46%
Piyush Chawla	21	9	229	366	495	100.00%
Yuzvendra Chahal	21	7	97	317	432	48.53%
Tushar Deshpande	21	10	137	341	564	52.50%

Table 14b Bowling model – final DEA results using solver on output 3 (dot balls) (continued)
(see online version for colours)

<i>Bowler</i>	<i>Bowling data</i>					
	<i>Outputs</i>			<i>Inputs</i>		<i>Efficiency</i>
	<i>Wickets</i>	<i>Matches won</i>	<i>Dot balls</i>	<i>Balls bowled</i>	<i>Runs conceded</i>	
Ravindra Jadeja	20	10	107	342	431	53.65%
Varun Chakravarthy	20	6	124	316	429	62.47%
Mohammad Siraj	19	7	161	312	376	92.54%
Matteesha Pathirana	19	8	104	278	371	60.58%
Arshdeep Singh	17	6	114	305	493	49.98%
Ravi Bishnoi	16	8	97	303	391	53.62%
Noor Ahmad	16	8	103	283	369	60.33%
Bhuvneshwar Kumar	16	4	128	306	425	65.09%
Ravichandran Ashwin	14	6	90	294	368	52.86%
Akash Madhwal	14	5	53	153	219	52.30%
Jason Behrendorff	14	6	92	252	387	51.38%
Harshal Patel	14	6	87	282	454	41.42%
Trent Boult	13	5	107	228	312	74.12%
Deepak Chahar	13	7	82	204	297	59.67%
	-	-	0.004366	-	0.002020	1.00
	1.00					

Table 15a Bowling model – initial goal seek results on output 2 (matches won)
(see online version for colours)

<i>Bowler</i>	<i>Bowling data</i>					
	<i>Outputs</i>			<i>Inputs</i>		<i>Efficiency</i>
	<i>Wickets</i>	<i>Matches won</i>	<i>Dot balls</i>	<i>Balls bowled</i>	<i>Runs conceded</i>	
Mohammad Shami	28	11	193	390	522	100.00%
Mohit Sharma	27	9	87	265	361	100.00%
Rashid Khan	27	11	134	402	552	84.77%
Piyush Chawla	21	12.30461066	121	366	495	100.00%
Yuzvendra Chahal	21	7	97	317	432	71.43%
Tushar Deshpande	21	10	137	341	564	79.84%
Ravindra Jadeja	20	10	107	342	431	94.28%
Varun Chakravarthy	20	6	124	316	429	70.63%
Mohammad Siraj	19	7	161	312	376	96.44%
Matteesha Pathirana	19	8	104	278	371	93.03%
Arshdeep Singh	17	6	114	305	493	60.90%
Ravi Bishnoi	16	8	97	303	391	86.17%
Noor Ahmad	16	8	103	283	369	92.97%
Bhuvneshwar Kumar	16	4	128	306	425	57.81%

Table 15a Bowling model – initial goal seek results on output 2 (matches won) (continued)
(see online version for colours)

<i>Bowling data</i>						
<i>Bowler</i>	<i>Outputs</i>			<i>Inputs</i>		<i>Efficiency</i>
	<i>Wickets</i>	<i>Matches won</i>	<i>Dot balls</i>	<i>Balls bowled</i>	<i>Runs conceded</i>	
Ravichandran Ashwin	14	6	90	294	368	72.74%
Akash Madhwal	14	5	53	153	219	94.23%
Jason Behrendorff	14	6	92	252	387	71.63%
Harshal Patel	14	6	87	282	454	60.35%
Trent Boult	13	5	107	228	312	82.14%
Deepak Chahar	13	7	82	204	297	100.00%
-		0.062478	0.001911	0.000381	0.001738	1.00
1.00						

Table 15b Bowling model – final DEA results using solver on output 2 (matches won)
(see online version for colours)

<i>Bowling data</i>						
<i>Bowler</i>	<i>Outputs</i>			<i>Inputs</i>		<i>Efficiency</i>
	<i>Wickets</i>	<i>Matches won</i>	<i>Dot balls</i>	<i>Balls bowled</i>	<i>Runs conceded</i>	
Mohammad Shami	28	11	193	390	522	100.00%
Mohit Sharma	27	9	87	265	361	99.90%
Rashid Khan	27	11	134	402	552	84.55%
Piyush Chawla	21	12.305	121	366	495	100.00%
Yuzvendra Chahal	21	7	97	317	432	71.29%
Tushar Deshpande	21	10	137	341	564	77.75%
Ravindra Jadeja	20	10	107	342	431	95.22%
Varun Chakravarthy	20	6	124	316	429	70.46%
Mohammad Siraj	19	7	161	312	376	97.86%
Matteesha Pathirana	19	8	104	278	371	93.14%
Arshdeep Singh	17	6	114	305	493	59.41%
Ravi Bishnoi	16	8	97	303	391	86.70%
Noor Ahmad	16	8	103	283	369	93.39%
Bhuvneshwar Kumar	16	4	128	306	425	57.41%
Ravichandran Ashwin	14	6	90	294	368	73.48%
Akash Madhwal	14	5	53	153	219	93.48%
Jason Behrendorff	14	6	92	252	387	70.36%
Harshal Patel	14	6	87	282	454	58.94%
Trent Boult	13	5	107	228	312	81.84%
Deepak Chahar	13	7	82	204	297	98.97%
-		0.062652	0.001893	-	0.002020	1.00
1.00						

Further analysis using Solver revealed that Chawla could achieve 100% efficiency if his team won approximately 12.30 matches instead of the current 9. This scenario is depicted in Table 15a.

Running Solver with this updated input revealed changes to the efficiency frontier. Table 15b shows that the revised frontier now includes Chawla, Mohammad Shami, and Mohit Sharma. This reinforces the pattern seen across other analyses: the efficiency frontier evolves as specific DMUs improve, impacting the relative standing of others.

6.2.2 *Bowling: managerial implications*

As per Table 13, the DEA results highlight that two outputs – dot balls and runs conceded – have non-zero coefficients, confirming their relevance. However, the third output, ‘wickets’, is currently irrelevant due to a zero coefficient. Table 16 presents the Sensitivity Report, which shows an allowable increase of 3.76 for this variable. If Chawla were to take more than 24.77 wickets, output 1 (wickets) would become relevant. This adjustment is confirmed by Solver and documented in Table 17.

Table 16 Bowling model – sensitivity report

<i>Cell</i>	<i>Name</i>	<i>Final value</i>	<i>Reduced cost</i>	<i>Allowable increase</i>	<i>Allowable decrease</i>
Output 1	Wickets	0	−3.76241236	3.76241236	1E+30
Output 2	Matches won	0.062477803	0	0.630390437	0.941640255
Output 3	Dot balls	0.001911033	0	29.48962882	7.920472524
Input 1	Balls bowled	0.000381455	0	7.952553958	0.583480963
Input 2	Runs conceded	0.001738157	0	0.78913409	10.7555033

Table 17 Bowling model – adding allowable increase to output 1 to make its corresponding coefficient relevant (see online version for colours)

<i>Bowling data</i>						
<i>Bowler</i>	<i>Outputs</i>			<i>Inputs</i>		<i>Efficiency</i>
	<i>Wickets</i>	<i>Matches won</i>	<i>Dot balls</i>	<i>Balls bowled</i>	<i>Runs conceded</i>	
Mohammad Shami	28	11	193	390	522	100.00%
Mohit Sharma	27	9	87	265	361	100.00%
Rashid Khan	27	11	134	402	552	83.83%
Piyush Chawla	24.77	9	121	366	495	79.36%
Yuzvendra Chahal	21	7	97	317	432	73.05%
Tushar Deshpande	21	10	137	341	564	91.81%
Ravindra Jadeja	20	10	107	342	431	83.40%
Varun Chakravarthy	20	6	124	316	429	75.18%
Mohammad Siraj	19	7	161	312	376	90.85%
Matteesha Pathirana	19	8	104	278	371	89.79%
Arshdeep Singh	17	6	114	305	493	73.26%
Ravi Bishnoi	16	8	97	303	391	78.57%

Table 17 Bowling model – adding allowable increase to output 1 to make its corresponding coefficient relevant (continued) (see online version for colours)

<i>Bowling data</i>						
<i>Bowler</i>	<i>Outputs</i>			<i>Inputs</i>		<i>Efficiency</i>
	<i>Wickets</i>	<i>Matches won</i>	<i>Dot balls</i>	<i>Balls bowled</i>	<i>Runs conceded</i>	
Noor Ahmad	16	8	103	283	369	85.96%
Bhuvneshwar Kumar	16	4	128	306	425	66.20%
Ravichandran Ashwin	14	6	90	294	368	67.06%
Akash Madhwal	14	5	53	153	219	97.68%
Jason Behrendorff	14	6	92	252	387	78.93%
Harshal Patel	14	6	87	282	454	68.99%
Trent Boult	13	5	107	228	312	85.30%
Deepak Chahar	13	7	82	204	297	100.00%
	0.004969	0.042624	0.002371	0.002732	-	0.79
	1.00					

Based on the above analysis, the Manager of the team that Chawla plays for can scrutinise the current team structure and take policy level decisions on how to make Chawla as close to 100% efficient as possible.

This comprehensive bowling analysis reinforces the adaptable nature of DEA, where small, data-driven modifications in inputs or outputs can result in significant shifts in the efficiency frontier. By tailoring performance improvements for individual players like Chawla or Ishan, management can not only enhance individual output but also redefine team-level benchmarks. The integration of tools such as Goal Seek, Solver, and sensitivity analysis provides actionable insights for informed decision-making and continuous optimisation of player performance.

7 Our contributions and conclusions

Using actual T20 2023 cricket data, our DEA analysis successfully evaluated the performance efficiency of individual players – both batters and bowlers. DEA proved to be a powerful tool in identifying not only the current efficiency levels of each player but also their relative inefficiencies. By establishing efficiency frontiers, we pinpointed those players operating at 100% efficiency. Furthermore, the model provided a framework to strategise operational improvement plans for underperforming players. The use of sensitivity reports added a valuable layer of insight, significantly strengthening the depth and precision of our quantitative analysis.

This DEA model can serve as a practical analytical tool for team owners, managers, and coaches to make data-driven decisions during player auctions and draft seasons. By offering a clear, objective measure of player efficiency, it supports smarter investment strategies, enabling teams to allocate budgets more effectively. Ultimately, this approach helps maximise return on investment by identifying high-performance players who provide the greatest value per unit cost, in the specific example of cricket in sports

management, which, in general, can be expanded to other industries in service management

This paper makes several unique contributions to both theory and practice. Theoretically, it extends the application of DEA to individual-level performance evaluation in T20 cricket, integrating sensitivity analysis to enhance robustness and interpretability within a sports analytics context. It also demonstrates how DEA can accommodate heterogeneous player roles within a unified efficiency framework. Managerially, the study provides a replicable, Excel-based decision-support model that translates efficiency scores into actionable improvement targets and investment insights. By bridging quantitative modelling with strategic resource allocation, the paper offers a scalable framework adaptable to broader service and performance-driven industries.

8 Future research

8.1 *Expanding DEA applications in cricket*

Performance evaluation in cricket has been approached through various analytical methods, including reliability analysis and stochastic Bayesian models (Koulis et al., 2014). For example, data from 20 players representing different countries has been analysed to capture underlying performance dynamics. While such techniques have been applied to One Day Internationals (ODIs), they could be adapted to the Twenty20 format to capture unique performance characteristics in shorter matches, using such advanced techniques. Another promising approach is social network analysis, which assesses the efficiency of both batters and bowlers by focusing on the quality of performance rather than quantity (Mukherjee, 2014). For instance, runs scored against top-quality opposition or wickets taken against strong teams receive higher value, enabling a more nuanced performance evaluation. We can extend our analysis for a quality-based study.

Future research could also incorporate additional contextual and strategic metrics to enrich player efficiency evaluation. For batters, variables such as batting order position, performance under powerplay or death overs, and match-winning innings could provide deeper insight into situational impact. For bowlers, analysing effectiveness in opening versus closing overs, performance under high-pressure conditions, and ability to contain runs in crucial phases would add further nuance. Beyond on-field metrics, factors such as fan popularity, leadership influence, and brand value may capture commercial and psychological dimensions of performance. Integrating these variables within a DEA or hybrid framework would enable a more holistic assessment of player efficiency. Current sources of data do not contain the necessary information for us to conduct these new analyses. In future, with more elaborate data availability, such analyses may be possible.

8.2 *DEA in other sports*

DEA has been used in sports such as football/soccer to evaluate the efficiency of resource allocation, particularly in the context of revenue distribution (Zambom-Ferraresi et al., 2017). Applying DEA to revenue allocation can help identify strategies for improving the efficiency of underperforming clubs. Our future work may explore advanced DEA methods, such as bootstrapped DEA, to provide more statistically robust assessments of performance and resource utilisation in professional sports.

8.3 DEA in other industries (e.g., healthcare)

In healthcare, DEA can be instrumental in addressing inefficiencies caused by the misallocation of health inputs and inadequate resource availability (Shetty and Pakkala, 2010). By developing DEA models that measure and control the use of healthcare resources, policymakers and administrators can identify areas of inefficiency and improve service delivery. Furthermore, the choice of input variables can significantly influence efficiency outcomes, highlighting the need for careful model design. Our future applications of DEA in healthcare should focus on optimising input usage to maximise output quality and accessibility of medical services.

Declarations

All authors declare that they have no conflicts of interest.

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