Asian Journal of Applied Science and Technology (AJAST)
Volume 9, Issue 3, Pages 214-222, July-September 2025

Design of Experiments and Regression Models in Sports Analytics: A Review with Focus on Cricket

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DOI: https://doi.org/10.38177/ajast.2025.9319

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Article Received: 16 July 2025 Article Accepted: 22 September 2025 Article Published: 28 September 2025

ABSTRACT

Cricket analytics has evolved from descriptive statistics to advanced predictive models, transforming how teams strategize and evaluate performance. Traditional regression-based approaches provided interpretable insights but were often limited in capturing the complex interactions among match factors. More recent developments in machine learning, such as Random Forests, Support Vector Regression (SVR), and Neural Networks, have achieved higher predictive accuracy (65.2-90%) but at the cost of interpretability.

This review synthesizes over fifteen studies that apply regression, machine learning, and simulation methods to cricket outcome prediction. A consistent finding across the literature is that while algorithms like Random Forest and Gradient Boosted Trees outperform probabilistic models in accuracy, factorial frameworks such as Design of Experiments (DoE) and Response Surface Methodology (RSM) remain underexplored despite their potential for capturing interactions among variables such as venue, toss, and match conditions.

Key gaps identified include limited application of DoE in modern cricket analytics, insufficient focus on rain-affected matches, underrepresentation of women's cricket, and lack of momentum-based models. The review proposes integrating DoE with regression and machine learning to create hybrid models that strike a balance between predictive accuracy and interpretability. Such models can inform real-time coaching strategies, improve fairness in score adjustments, and extend predictive analytics to broader sports contexts.

Keywords: Cricket Analytics; Design of Experiments (DoE); Factorial Designs; Machine Learning (ML); Predictive Modelling; Response Surface Methodology (RSM); Regression Modelling; Sports Statistics; Sports Analytics; Support Vector Regression (SVR).

1. Introduction

Cricket, one of the most widely played sports worldwide, has undergone a significant shift in recent decades, marked by the increasing integration of data analytics, statistics, and machine learning into strategy, performance evaluation, and decision-making. While cricket has always been influenced by contextual variables such as pitch conditions, toss outcome, match format, and weather, early studies often relied on descriptive statistics and expert intuition. The academic foundation for quantitative analysis in cricket was laid by Clarke and Bailey [1], who introduced Bayesian hierarchical models to assess team strength and player performance. Their work demonstrated that probabilistic methods could improve accuracy in predicting match outcomes compared to traditional averages. Also, Bandulasiri [2] applied logistic regression to study One-Day International (ODI) outcomes, incorporating variables such as toss, home advantage, and Duckworth–Lewis (D/L) adjustments. These pioneering contributions revealed both the potential and limitations of traditional regression-based approaches in sports analytics.

The rapid expansion of Twenty20 (T20) cricket, particularly the Indian Premier League (IPL) and international T20Is, generated massive volumes of high-frequency ball-by-ball data. This shift created opportunities for researchers to apply machine learning (ML) and big data techniques to capture complex, nonlinear interactions. For example, Awan et al. [3] integrated Spark-based distributed computing with Gradient Boosted Trees to handle large-scale cricket datasets, achieving accuracy above 84%. While these models improved predictive power, they often lacked interpretability, limiting their utility for coaches and decision-makers. Kapadia et al. [4] compared

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Naïve Bayes, KNN, and Random Forest classifiers for IPL outcome prediction, highlighting that ensemble models consistently outperform simpler statistical approaches.

In parallel, scholars began exploring Design of Experiments (DoE) frameworks to address the limitations of black-box ML models. A landmark study by Shah et al. [5] applied a full factorial design ($2^2 \times 3^2$) to analyse the role of venue, toss, decision, and match conditions in T20I cricket. Using stepwise regression, the authors found that toss decision, particularly when interacting with venue, explained nearly 67% of the variance in successful run chases. This structured factorial approach uncovered nuanced relationships that single-factor or purely algorithmic models often fail to detect. Likewise, Chougale et al. [6] employed Response Surface Methodology (RSM) to model rain-interrupted matches, presenting a statistically robust alternative to the Duckworth–Lewis–Stern (DLS) method. Their nonlinear regression approach showcased the practicality of DoE-inspired models in addressing operational issues in cricket. Other contributions expanded the methodological toolkit. Gupta [7] developed a Principal Component Analysis (PCA)-based batting index for women's cricket, integrating dimensionality reduction with regression. Wickramasinghe [8] employed Naïve Bayes classifiers for ODI outcome prediction. Beyond cricket, momentum- based analytics, such as Chen et al. [9] in tennis, illustrate the potential of exploratory factor analysis in quantifying performance dynamics, which could be adapted for cricket contexts.

Despite these advancements, several research gaps persist. First, the majority of models prioritize prediction accuracy but neglect explainability—a crucial factor for real-world decision-making in cricket. Second, very few studies combine DoE principles with modern ML models to create hybrid frameworks capable of capturing both interaction effects and nonlinear dynamics. Third, most research has focused on men's cricket, leaving women's cricket and associate nations underexplored. Finally, while operational models like DLS or RSM offer fairness in special scenarios, their integration into predictive frameworks remains incomplete.

Thus, this review synthesizes the contributions of DoE and regression modelling in cricket analytics, comparing them with machine learning and big data approaches. By critically examining 15+ key studies, we aim to highlight the strengths, limitations, and complementarities of different methodologies. Ultimately, this review sets the stage for future research that integrates factorial experimentation, regression models, and machine learning into a unified predictive framework—one that balances accuracy, interpretability, and practical utility for cricket and other sports.

1.1. Study Objectives

1. To critically review the evolution of cricket analytics from traditional regression and probabilistic models to advanced machine learning and hybrid approaches.

2. To evaluate the role of Design of Experiments (DoE) and Response Surface Methodology (RSM) in addressing fairness issues such as rain-interrupted matches.

3. To compare predictive accuracies of regression-based models, ensemble methods, and big data–enabled algorithms in cricket outcome prediction.

4. To identify methodological gaps, particularly the underutilization of factorial frameworks and hybrid models that balance accuracy with interpretability.

5. To highlight emerging areas in cricket analytics, including women's cricket, franchise leagues, and momentum-based performance indices.

6. To propose future directions for integrating DoE, regression, and machine learning into a unified framework for real-time decision-making and fair outcome estimation in cricket.

2. Literature Review

2.1. Early Statistical Foundations (pre-2010)

One of the earliest contributions to cricket analytics was made by Clarke and Bailey [1], who introduced the use of Markov chain models to study batting outcomes. Their approach modelled a cricket innings as a sequence of stochastic events—such as runs scored, wickets lost, or dot balls—where the probability of each outcome depended on the current state. This sequential modelling was groundbreaking because it captured the dynamic nature of cricket rather than treating the game as a static set of averages. Importantly, it allowed analysts to estimate win probabilities at any stage of a match, which was a considerable step forward from traditional averages-based statistics. However, despite its novelty, the model faced limitations. First, the Markov approach assumes that the probability of future states depends only on the current state, which ignores the influence of contextual match conditions such as toss results, venue, and weather. For example, a team's batting performance under day/night conditions or against a particular opposition bowling attack might differ significantly, but the model could not capture such interaction effects.

Moving beyond purely sequential models, Bandulasiri [2] applied logistic regression to predict ODI match outcomes. His study included variables such as home advantage, toss outcome, toss decision, and match type, making it one of the first works to link contextual match factors with statistical modelling explicitly. Importantly, he also examined the Duckworth–Lewis (D/L) method for rain-affected matches, highlighting its biases and limitations. He argued that regression-based approaches could offer more fairness and transparency in outcome estimation compared to purely rule-based systems. The results indicated that toss outcome and home advantage were significant predictors, confirming the widely held belief in cricket that these factors shape match results. However, the model's predictive power was limited due to small datasets and a reliance on simple main-effect regressions without interaction terms.

2.2. Rain Rule Adjustments and Fairness Studies

Rain interruptions have long been a challenge for cricket statisticians, with the Duckworth–Lewis (D/L) method often criticized for being opaque and biased. To address this, Chougale et al. [6] applied Response Surface Methodology (RSM), an experimental design technique, to propose a more transparent model for adjusting targets in rain-affected matches. Their method explicitly modelled the relationships between overs lost, stage of the innings, and batting order, producing a nonlinear regression surface that could estimate fairer scores. The study's strength lay in its application of DoE principles to systematically vary and test combinations of overs lost and match stage, rather than relying on ad-hoc adjustments. By using RSM, the researchers showed that the impact of losing overs in the middle phase of an innings was more detrimental than losing the same number at the start or end. This insight had clear implications for rule-making, as it allowed for context-specific adjustments instead of uniform penalties.

2.3. Machine Learning Approaches in Cricket Analytics

Kapadia et al. [4] conducted one of the first comprehensive comparative machine learning studies using IPL datasets. Their work evaluated Naïve Bayes, K-Nearest Neighbours (KNN), Random Forest, and Model Trees for predicting match outcomes. The feature set included both player-level attributes (runs scored, wickets taken, strike rate) and contextual variables (home/away, toss result). The study found that Random Forest achieved the highest accuracy (79.5%), outperforming probabilistic classifiers like Naïve Bayes. However, one of the critical findings was that coin toss outcomes disrupted predictive accuracy, as no algorithm could reliably account for its randomness. This result exposed a key limitation of ML models that focus purely on feature selection and prediction: they often lack causal interpretability.

Mahajan et al. [10] incorporated current form, home advantage, and player statistics into supervised learning models for outcome prediction in IPL. Algorithms included Random Forest, Naïve Bayes, KNN, and Gradient Boosted Decision Trees (GBDTs). Their results showed that GBDT and Random Forest consistently outperformed statistical classifiers, with accuracies above 80%. The novelty of their study lay in the estimation of team strength through aggregated player metrics, essentially creating a composite team index. This was a step toward dimensionality reduction, though it was not formalized as PCA. The authors also recommended sentiment analysis from social media as an additional predictive feature, though this was outside their core experiments.

Tekade et al. [11] expanded the scope of prediction by testing a wide range of supervised ML algorithms, including Decision Trees, Bayes Networks, Logistic Regression, SVMs, Linear Regression, and Random Forest on IPL datasets. Their study highlighted that while multiple models could achieve reasonable accuracy, the Random Forest once again emerged superior with ~90% accuracy, confirming earlier findings by Mahajan et al. [10]. An important contribution was their analysis of regression-based approaches within ML. They noted that regression models performed reasonably well for score prediction but struggled with categorical classification tasks like win/loss outcomes. This distinction provided useful methodological clarity: while ML classifiers are effective for categorical outcomes, regression models retain utility for continuous variables like first-innings totals.

2.4. Regression and Hybrid Approaches in Cricket Analytics

Chougale et al. [6] tackled the practical challenge of rain-interrupted matches using a regression-based model with Response Surface Methodology (RSM). Their factors included overs lost, innings stage, and batting order, and the goal was to recalculate target scores more fairly than the Duckworth-Lewis-Stern (DLS) method.

The RSM-based nonlinear regression took the form:

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i<j} \beta_{ij} x_i x_j + \varepsilon \qquad (1)$$

where Y was the adjusted score, and X_i represented overs remaining, wickets lost, etc. The model given in equation (1) offered continuous, nonlinear adjustments, unlike DLS, which often led to discontinuities and unfair outcomes.

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Thorat et al. [12] focused specifically on first-innings score prediction using regression techniques. Their study highlighted the importance of overs completed, wickets lost, and runs scored in the last 5 overs as critical predictors. The chosen model was Linear Regression, which explained approximately 75% of the variance in scores with acceptable error margins. Although simple, their work demonstrated the predictive utility of regression methods for continuous cricket outcomes, such as runs, rather than binary win/loss results. The limitation was the assumption of linearity, which restricted the ability to capture nonlinear interactions such as "wickets lost × overs remaining."

Bhor et al. [13] adopted a multi-factor regression and ensemble approach for cricket outcome prediction. Their feature set included ground conditions, historical player statistics, and venue-specific performance records. The authors proposed a "master factor" model where the combined weighted importance of key features drove predictions. Methodologically, they experimented with Naïve Bayes, ensemble classifiers, and Euler's strength formula. Their findings emphasized that ensemble methods outperformed single models, but performance varied depending on the relative weight assigned to contextual features.

Awan et al. [3] tackled cricket prediction using a Big Data architecture integrated with ML. They applied Gradient Boosted Trees (GBT) and Random Forest within Apache Spark, enabling scalable processing of large cricket datasets. Their model achieved over 84% accuracy for winner prediction, with error metrics (RMSE, MAE) consistently outperforming traditional ML models. The novelty of their approach was parallelized real-time prediction, demonstrating how big data infrastructures can bring ML into operational decision-making during live matches. However, the study lacked a structured experimental design; while predictive power was strong, interpretability of causal factors remained weak.

Srikantaiah et al. [14] extended predictive modelling to IPL outcomes using Random Forest, Logistic Regression, SVM, and KNN. Their study incorporated both traditional match factors (toss, venue, day/night) and player-centric attributes (batting/bowling averages, prior match success). With Random Forest achieving 88.1% accuracy, their findings reinforced the superiority of tree-based models in cricket analytics. More importantly, they noted that player performance metrics alone were insufficient, and the integration of contextual features (e.g., toss and venue) markedly improved accuracy.

2.5. Feature Engineering, Dimension Reduction, and Regression Extensions

Gupta [7] focused on building a performance index for women's cricket using Principal Component Analysis (PCA) and Gini scores. The goal was to reduce dimensionality in player performance data (batting strike rate, averages, boundaries, consistency metrics) while retaining the most discriminative features. Mathematically, PCA transformed the high-dimensional performance data into a set of orthogonal components:

$$Z = W^T X \qquad (2)$$

where X represents the original feature matrix, and W contains the eigenvectors of the covariance matrix of X. The first few principal components explained most of the variance in player performance, effectively filtering out noise. The final batting performance index successfully ranked players more consistently than raw averages, highlighting PCA's utility in constructing interpretable metrics.

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Aldar et al. [15] explored real-time IPL score prediction using Random Forests and Support Vector Regression (SVR). Their dataset included overs completed, wickets lost, and run rate in the last 5 overs as dynamic features. The SVR model optimized the function:

$$\min \frac{1}{2}||w||^2 \quad \text{s.t.} \quad |y_i - (w \cdot x_i + b)| \leq \epsilon \qquad (3)$$

SVR achieved $R^2 = 0.84$ and RMSE = 11.9, significantly outperforming traditional regression ($R^2 < 0.65$). Random Forest also showed strong predictive stability.

2.6. Design of Experiments (DoE) Applications

Shah et al. [5] pioneered explicit DoE in cricket by applying a $2^2 \times 3^2$ factorial design with variables: toss outcome, toss decision, venue, and match condition. Using stepwise regression, they explained ~67% of the variance in successful run chases, with toss decision × venue interaction emerging as most significant. Focused only on run-chases; could be extended to player-level performance or interrupted matches.

3. Comparative Discussion

Sports analytics in cricket has progressed through diverse approaches, ranging from probabilistic models and regression to machine learning and simulation-based strategies. However, while accuracy-focused models dominate, relatively fewer studies emphasize interpretability and structured experimental design. Table 1 provides a consolidated comparison.

Table 1. Comparative Analysis of Reviewed Studies in Cricket Analytics

Year	Author(s)	Methodology	Dataset/ Context	Performance Metrics	Key Findings	Limitations/ Gaps
2006	Clarke & Bailey	Markov Chains	Test & ODI cricket	Accuracy = 68–74%	Foundational probabilistic model	Computationally simple, ignores context
2008	Bandulasiri	Logistic Regression	ODI outcomes	Classification accuracy ~ 70%	Identified biases in the D/L method	Limited modelling scope
2020	Chougale et al.	RSM (nonlinear regression)	Rain-affected ODIs	Adjusted scores are fairer than DLS	Improved the fairness of the rain rule	Limited to rain scenarios
2020	Kapadia et al.	RF, Naïve Bayes, KNN, Model Trees	IPL outcomes	Accuracy = 79.5%	RF is most reliable for classification	Interaction effects ignored
2020	Wickramasinghe	Naïve Bayes	ODI outcomes	Accuracy = 65.2%	Simple, baseline model	Assumes feature independence
2020	Tekade et al.	RF, SVM, Logistic Regression	IPL outcomes	Accuracy = 90%	RF most effective	No factorial insights
2021	Thorat et al.	Linear Regression	First-innings score	RMSE moderate	Runs/wickets predictive	Linear, ignored nonlinearities

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2021	Srikantaiah et al.	RF, SVM, Logistic Regression, KNN	IPL matches	Accuracy = 88.1%	RF outperformed others	No regression comparison
2022	Bhor et al.	Hybrid Regression + Ensembles	IPL/ODI	Conceptual framework	Suggested master feature weighting	No real dataset validation
2021	Awan et al.	Spark ML + RF, GBT	Big Data ODI matches	Accuracy > 84%	Real-time scalable pipeline	Causal inference absent
2022	Gupta	PCA + Gini Index	Women's cricket (batting index)	Variance explained > 70%	Created an interpretable batting performance index	No predictive testing under match conditions
2024	Aldar et al.	Random Forest, SVR	IPL score prediction	$R^2 = 0.84$; RMSE = 11.9	Dynamic features (overs, wickets, run rate) are strong predictors	No factorial design, focus only on accuracy
2024	Shah et al.	Full factorial DoE + Stepwise Regression	T20I matches (36 factorial scenarios)	$R^2 = 66.8\%$; Adj. $R^2 = 44.6\%$	Toss decision × venue interaction significant; factorial structure improved model fit	Limited to T20I, not IPL/ODI

4. Conclusion

This review highlights the evolution of cricket analytics from early regression models to modern machine learning and hybrid approaches. While machine learning has significantly improved predictive accuracy, it often sacrifices interpretability. Conversely, Design of Experiments (DoE) and regression methods provide statistical clarity but are rarely applied systematically in cricket contexts. Integrating these two approaches offer a promising pathway toward models that are both interpretable and accurate. Shah et al. [5] demonstrated how factorial DoE can reveal nuanced interactions between match conditions, toss outcomes, and venue. Aldar et al. [15] and Kapadia et al. [4] showed the predictive power of machine learning, while Chougale et al. [6] illustrated how RSM could enhance fairness in rain-interrupted matches. Collectively, these works underscore that the future of cricket analytics lies in hybrid, context-aware, and experimentally structured approaches. The proposed research aims to bridge this gap by integrating DoE-based factorial models with regression and advanced machine learning. Beyond cricket, the framework could be generalised to other sports where uncertainty and interaction effects shape outcomes. Ultimately, this research has the potential to contribute both to academic knowledge in statistical modelling and to practical innovations in sports strategy, coaching, and policymaking.

4.1. Future Suggestions

The following are some future suggestions concerning this study:

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1. Adopt Structured Experimental Designs: Implement and expand on full factorial designs and other Design of Experiments (DoE) frameworks to isolate and understand interaction effects between factors like toss, venue, and weather conditions.

2. Develop Interpretable Hybrid Models: Combine regression analysis and DoE with machine learning algorithms to build hybrid models that maintain both high predictive accuracy and interpretability, aiding better tactical decision-making.

3. Advance Rain-Interruption Methodologies: Extend and validate Response Surface Methodology (RSM) using large-scale datasets as a robust alternative to the DLS method for rain-affected matches.

4. Incorporate Women's Cricket and Franchise Leagues: Expand analytical models to include data from women's cricket and T20 franchise leagues, addressing the current underrepresentation despite their growing global significance.

5. Model and Quantify Momentum: Develop momentum indices for cricket by adapting advanced techniques such as factor analysis and Bayesian modelling, as employed in sports like tennis and baseball, to systematically capture psychological and performance shifts during matches.

Declarations

Source of Funding

This study received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Competing Interests Statement

The authors declare that they have no competing interests related to this work.

Consent for publication

The authors declare that they consented to the publication of this study.

Authors' contributions

Both the authors took part in literature review, analysis, and manuscript writing equally.

Availability of data and materials

Supplementary information is available from the authors upon reasonable request.

Ethical Approval

Not applicable for this study.

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