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An Integrative Linear Mixed Modeling Approach to *Batting* Performance in Cricket: Examining *Ball* Opportunities, *Run* Production, Match Context, and Individual Variability

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Abstract

Study Purpose: Batting evaluation in cricket is still dominated by conventional indicators such as total score, which potentially simplifies the performance-building mechanism and fails to integrate the relationships between balls, runs, run type, innings, match type, and individual athlete variation. This study aims to analyze the characteristics of performance distribution, the relationship between run type and innings, and the influence of match context using an integrative analytical framework.

Materials and methods: The study employed a retrospective observational design with a total-event sampling approach on 601 valid batting observations from all available match events. Analysis was conducted using descriptive statistics, performance distribution visualization, the Chi-Square test, and a Linear Mixed Model (LMM). The LMM approach was used to accommodate the multilevel data structure, repeated measurements, fixed effects, and individual athlete variation as random effects.

Result: The results show high heterogeneity in batting performance, marked by significant variation in ball and run distribution. Boundary scoring (4 runs and 6 runs) contributed more to the score than single runs, indicating a tendency toward aggressive play strategies in scoring. A significant relationship was found between run type and innings, although the effect size was relatively small. Linear Mixed Model results showed that match type and innings had no significant effect after individual athlete variation was accounted for.

Conclusion: Cricket batting performance is a multidimensional phenomenon shaped by the dynamic interaction of playing opportunities, scoring efficiency, match context, and individual athlete characteristics. These findings suggest that individual dynamics contribute more to performance formation than the general match context, supporting the use of integrative approaches and multilevel models in modern sports performance analysis.

Keywords: cricket batting, linear mixed model, match context, run production, sport analytics

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Introduction

The development of modern sports in recent years has demonstrated a major transformation toward a data-driven approach, where performance evaluation, decision-making, strategy development, and identification of competitive patterns increasingly rely on the analysis of performance data. This transformation has driven the development of sports analytics as a key instrument in modern sports systems. The integration of machine learning, deep learning, artificial intelligence, and predictive approaches has become a crucial part of the development of sports analytics (Jia et al., 2025; Pietraszewski et al., 2025). Furthermore, advances in motion tracking technology and computer-based visual systems have enabled the collection of performance data with increasingly high levels of precision (Barris & Button, 2008). This shifts the paradigm of sports evaluation from subjective observation to an evidence-based, scientific approach (Singh, 2020).

In sports performance analysis, the goal of modern research is no longer simply to describe the final outcome of a match, but also to identify the mechanisms that explain why a performance or victory occurs. This concept has evolved through the use of performance indicators, which are indicators used to understand the factors contributing to successful sports performance. However, performance indicators are not universal because they are influenced by game characteristics, competition demands, and different sports structures. Variations in match context are known to produce changes in competitive behavior and influence the performance indicators that emerge during play. Therefore, indicators that effectively explain performance in one sport may not be directly applicable to other sports.

Cricket is a highly complex sport because match performance is influenced by the interaction of various technical, tactical, situational, and competitive factors that dynamically evolve. Match success is influenced not only by an athlete's individual abilities but also by their ability to adapt to changing playing conditions during the match. In team-based sports, changes in athlete behavior and decisions often arise from interactions between players and the match context. In modern cricket era, batting performance is one of the crucial factor component in scoring and team success. Previous research has shown that batting performance is strongly correlated with match outcomes, particularly in fast-paced match formats.

However, batting performance evaluation was still dominated by conventional indicators such as total score or average performance match. This approach has the potential to produce overly simplistic interpretations because it fails to fully explain the mechanisms of score formation during a match. From a match perspective, balls can be viewed as representing playing opportunities, while runs represent the conversion of opportunities into performance output. Athletes with similar playing opportunities do not necessarily produce the same scoring productivity. Therefore, the relationship between playing opportunities and scoring productivity is a crucial component to understanding batting performance efficiency in match. Recent statistical analysis suggests that modern performance indicators in cricket are evolving toward evaluations based on scoring efficiency and performance contribution patterns (Mullick, 2024).

Based on the total score, the distribution of run types has the potential to provide additional information regarding the characteristics of an athlete's playing behavior. The 1-run score can reflect a conservative strategy based on gradual score accumulation, while 4-run and 6-run scores are often associated with aggressive play patterns through boundary scoring.

Differences in score distributions allow for the identification of distinct playing strategy characteristics across athletes. Previous research has shown that teams with higher boundary scoring contributions tend to have a greater probability of winning than teams relying solely on score accumulation. Furthermore, an action valuation-based evaluation approach also suggests that each game action contributes differently to the outcome of a match (Xarles et al., 2025).

On the other hand, sports performance is also influenced by contextual factors within the match. The literature shows that situational variables such as competition structure, match pressure, opponent quality, and playing conditions can produce changes in athlete behavior even when the observed individual is the same (Gómez et al., 2013). Variations in match context are also known to influence strategic patterns, game intensity, and athlete productivity during competition (Liu et al., 2016). Recent research also suggests that variations in game context can influence the distribution of specific events during a match (Xu et al., 2025).

In cricket, match context can emerge through various game formats such as T10, T20, and Last Man Standing (LMS), as well as through the innings phase of the match. Each format has distinct game characteristics due to variations in the number of overs, tempo of play, and competitive pressure. These variations can effect to game strategy, score distribution, and athlete decision-making patterns during the match. Recent research has shown that performance indicators in T20 are influenced by match context and specific game or phases, particularly regarding run-scoring patterns and game dynamics in the powerplay, middle overs, and death overs. Furthermore, situational contexts such as match decisions, playing conditions, and competitive factors are also known to influence team performance in T20 cricket. However, previous research has shown inconsistent findings. Some studies report that match context has a significant influence on match performance, while others find a relatively small contribution, leaving the mechanisms shaping batting performance still incompletely understood.

Another limitation from previous research is that most studies still analyze performance indicators separately. Most studies still focus on total scores, average performance, or a single indicator without simultaneously integrating the relationship between playing opportunities, run types, innings, and match context. Consequently, the mechanisms that shape batting performance during a match have not been comprehensively explained. This situation indicates a conceptual gap because the relationship between the components that shape performance is not fully understood.

In addition to conceptual gaps, there are also methodological gaps in modern sports research. Competition data generally has a hierarchical structure because a single athlete can generate repeated observations in different competitive situations. This structure creates interdependence between observations, potentially violating the independence assumption of traditional statistical approaches (Harrison et al., 2018). In the context of repeated measures and multilevel data, the use of conventional models can produce biased parameter estimates and statistical inference errors due to failure to consider intra-individual correlations and inter-subject variation (Gomes, 2022). Therefore, mixed-effects model-based approaches are increasingly recommended because they can simultaneously accommodate fixed effects, individual variation (random effects), and hierarchical data structures. Developments in modern sports methodology also demonstrate the increasing use of complex statistical models to understand the dynamics of match performance, multi-level relationships, and behavioral patterns of athletes in competitive situations (Midoul et al., 2026).

Based on the above description, this study offers an integrative analytical framework by combining the distribution of balls, runs, run types, innings, match types, and individual athlete variations in one analytical framework. The study also uses total-event sampling so that all match events can be maintained according to the natural structure of the data. Therefore, this study aims to identify the characteristics of the distribution of balls and runs, evaluate the distribution of run types by innings, examine the relationship between run types and innings, 25 and analyze the effect of match types and innings on performance using a Linear Mixed Model. This structure is expected to expand the literature on sport performance analysis in cricket and provide a more comprehensive data-driven evaluation approach.

Materials and methods

The research data consisted of 601 valid batting observations obtained from all available match events in the analyzed competition. The study used a total-event sampling approach, meaning all available matches, all innings, and all available batting events were included in the analysis for a single team.

Total-event sampling was chosen because this approach minimizes selection bias, maintains the natural structure of the competition, and increases the representativeness of sports performance data (Lago-Peñas et al., 2013). Furthermore, using all match observations is considered more appropriate for identifying actual athlete behavior patterns than using a subset of match events (sub-sampling) (McGarry, 2009).

The research unit of analysis is batting events that occur during a match. The research variables consist of:

- Balls: number of balls faced by the athlete
- Total Runs: total score produced
- 1 Run: frequency of single scores
- 4 Runs: frequency of four-point boundary scores
- 6 Runs: frequency of six-point boundary scores
- Innings: phase of play (innings 1 and 2)
- Match Type: match format (T10, T20, LMS)

The selection of these indicators is based on previous research showing that match context and score production indicators are important factors in cricket batting performance (Noorbhai & Noakes, 2016).

Study participants

The research subjects consisted of 11 male players who were members of the Malang City Porprov Cricket team. Subject selection was conducted using total sampling technique, involving players registered in the East Java Official 2025 Provincial Games Competition. The inclusion criteria were as follows: (1) male with a maximum age of 23 years; (2) registered as an official athlete of the Malang City Porprov team; (3) playing as a main batsman or all-rounder; (4) having complete performance data recorded in the official scoresheet; and (5) participating in matches with a minimum format of 10 overs so that the score distribution can be analyzed representatively. The establishment of these criteria refers to cricket performance research standards that emphasize the importance of active player representation and data integrity (Scarf et al., 2010).

Study organization

The research procedure was carried out in several analytical stages, systematically structured based on the research objectives. The first stage involved extracting and organizing match data into a research database. All observations were then checked to identify completeness and ensure there were no duplicates or missing data.

9 The second stage involved descriptive analysis using the mean, standard deviation, minimum, and maximum values to evaluate the basic characteristics of batting performance. Visual analysis was then performed using the distribution of average runs against the athlete's total score and the distribution of runs against ball usage. Visualization was used because it can identify match performance variations and behavioral patterns often invisible through conventional statistics (Gómez et al., 2013).

The third stage grouped run types based on match innings to evaluate the frequency distribution of scores. The fourth stage evaluated the relationship between run types and innings using association analysis. Finally, a Linear Mixed Model-based modeling was conducted to evaluate the influence of match context on performance, taking into account individual athlete variation. The structure of the analysis stages was designed to systematically explore the relationship between the research questions, analysis procedures, and interpretation of the results.

Statistical analysis

Descriptive statistical analysis was used to evaluate the characteristics of the data distribution through the mean, standard deviation, minimum, and maximum values. Descriptive statistics are used as an initial approach to understand central tendency and the degree of variation between observations (Field, 2013).

Pearson Chi-Square analysis was used to evaluate the relationship between run type distribution and match innings. This test was chosen because it is suitable for use with categorical data and allows for the evaluation of frequency distribution relationships between groups. In addition to statistical significance testing, effect sizes were evaluated using Cramer's V. Reporting effect sizes is recommended in sports research because statistical significance values do not always reflect the practical meaning of research results (Lakens, 2013).

Prior to model analysis, assumptions were tested by evaluating the normality of residuals and homoscedasticity. Residual normality was checked using residual statistical tests and Q-Q plots, while homoscedasticity was checked using residual distribution plots. Visual evaluation is recommended because it can detect patterns of deviation that are not always identified by a single statistical test (Gelman & Hill, 2006).

The final stage involved pairwise comparisons using estimated marginal means to evaluate differences between match groups and innings. Analysis was conducted on Inning 1 versus Inning 2, T10 versus T20, T10 versus LMS, and T20 versus LMS. Results are presented as mean differences, standard errors, 95% confidence intervals, and significance values.

All analyses were conducted using IBM SPSS Statistics version 29 with a statistical significance level set at $\alpha < 0.05$.

Results

Ball Distribution and Run

Descriptive analysis was conducted to evaluate the basic characteristics of batting performance based on ball usage and runs. Table 1 shows that the average ball usage was 10.59±7.78 with a range of 1–34 balls, while the average run was 10.73±10.785 with a range of 0–39. In the score components, the average for 1 run was recorded at 2.73±3.113, 4 runs at 4.14±5.499, and 6 runs at 3.86±5.655. These statistics provide an initial overview of the trend in performance distribution and the variation in results produced during the match.

Table 1. Distribution Ball and Run

Var	Mean±SD	Minimum	Maximum
Ball	10.59±7.78	1	34
Run	10.73±10.785	0	39
1 *Run*	2.73±3.113	0	13
4 *Run*	4.14±5.499	0	20
6 *Run*	3.86±5.655	0	18

All variables show relatively high standard deviations compared to their means. This indicates a significant variation in performance across observations. The wide range of scores, especially for the runs variable, suggests that scoring ability is not evenly distributed. Additionally, the higher means of 4 runs and 6 runs compared to 1 run indicate that scoring contributions often come more from boundary scoring. These findings show diversity in batting patterns and highlight differences in playing strategies among athletes.

Average Distribution of Runs to Total Runs per Athlete

The distribution of average runs to the athlete's total score was analyzed to evaluate the relative contributions of 1 run, 4 runs, and 6 runs. Figure 1 shows variation in the proportion of scores across athletes, with some players being predominantly single runs, while others exhibited a greater boundary contribution.

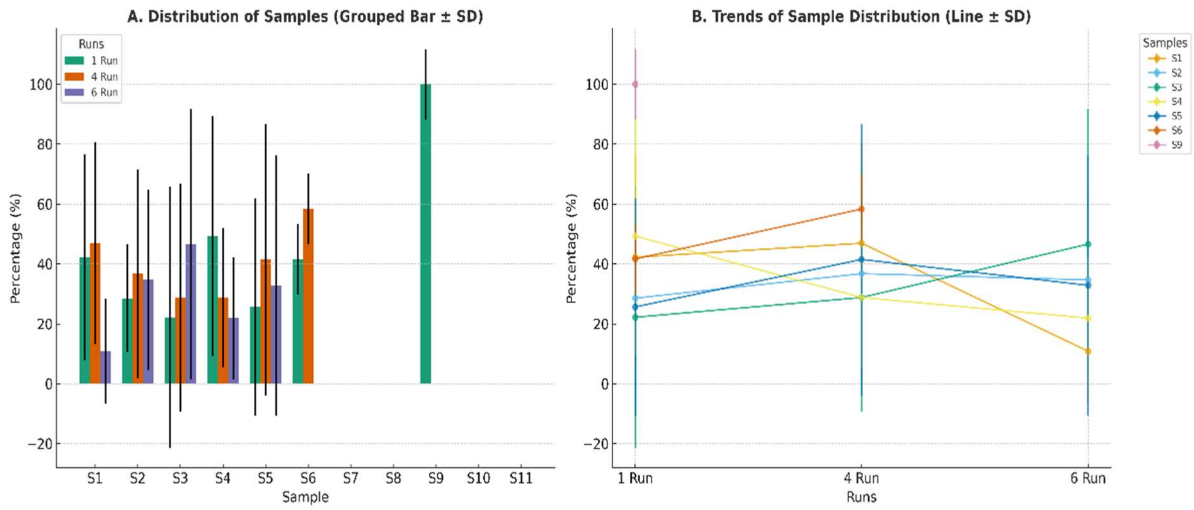

Figure 1. Average Distribution of Runs to Total Runs Per Athlete

The varying distribution patterns indicate heterogeneity in batting characteristics across athletes. The differences in contributions of 1 run, 4 runs, and 6 runs indicate that scoring does not follow a uniform pattern, thus indicating variations in playing strategies in shaping total scoring.

Average Runs Distribution to Ball

The distribution of runs relative to ball usage was analyzed to evaluate scoring patterns relative to the number of play opportunities. Figure 2 shows the variation in ball usage across each run category, with different distributions across athletes and scoring categories.

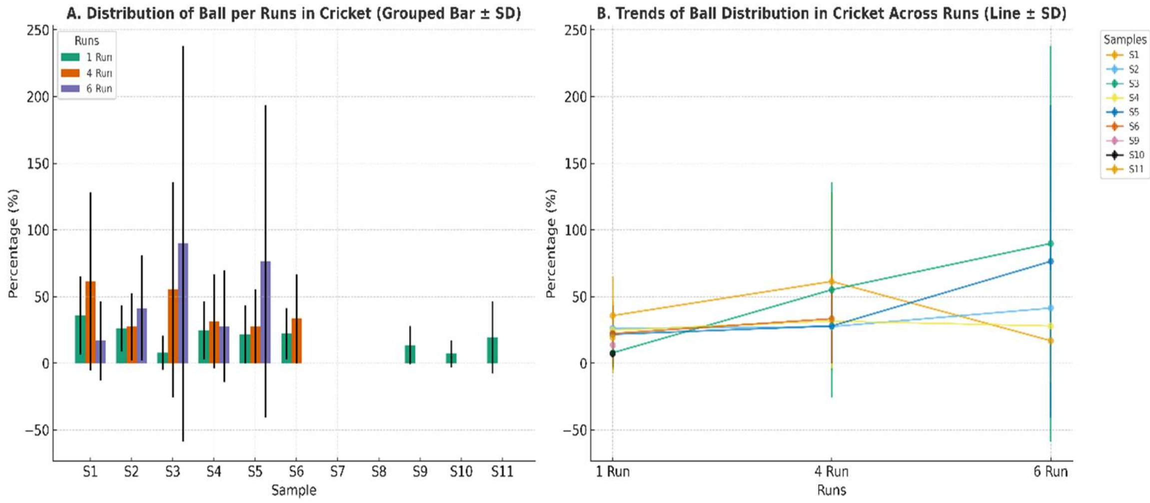

Figure 2. Average Runs Distribution to Ball

The variation in distribution indicates that ball usage does not produce a uniform scoring pattern across athletes. The differences in trends across run categories indicate heterogeneity in batting efficiency in converting play opportunities into runs.

Run Type per Inning

The distribution of run types by inning was analyzed to evaluate the pattern of scoring contributions across the two phases of play. Table 2 shows that 4 runs had the highest frequency (n=332), followed by 6 runs (n=216) and 1 run (n=153), with a higher occurrence in the first inning.

Table 2. Run Type per Inning

Run Type	Inning 1 (Count)	Inning 2 (Count)	Total
1 Run	90	63	153
4 Run	152	80	332
6 Run	156	60	216

Descriptively, the first inning showed a higher frequency of scoring than the second inning across all run categories. The dominance of 4-run and 6-run runs indicates a tendency for boundary scoring to contribute more to the total score than the accumulation of single runs.

Chi-Square Results

A chi-square test was performed to evaluate the relationship between run type and inning distribution. The results showed a significant relationship for total runs (χ^2=7.272; p=0.026), 1 run (χ^2=5.024; p=0.025), and 6 runs (χ^2=5.425; p=0.020), while 4 runs showed no statistical significance (χ^2=0.084; p=0.772).

Table 3. Chi-Square Results

Run Type	Pearson Chi Square	df	Sig. (2-sided)	Cramer's V	N Valid
Total Run	7.272	2	0.026	0.110	601
1 Run	5.024	1	0.025	0.091	601

4 Run	0.084	1	0.772	0.012	601
6 Run	5.425	1	0.020	0.095	601

Although some categories showed statistical significance, low Cramer's V values (0.012–0.110) indicated a weak effect size. This finding suggests that differences in run distributions between innings are statistically detectable, but the contribution of the resulting relationship is relatively small in practical terms.

Descriptive Statistics for Linier Mixed Models

Descriptive statistics are presented to describe the characteristics of the data based on the match type before the Linear Mixed Model modeling was performed. Table 4 shows that the highest average was found in LMS (1.21±0.81), followed by T10 (1.05±1.24), while T20 showed the lowest average (0.50±0.44).

Table 4. Descriptive Statistics for Liniear Mixed Models

Match Type	*n*	Mean	Standard Deviation
T10	22	1.05	1.24
T20	17	0.50	0.44
LMS	17	1.21	0.81

Descriptively, there is variation in the average between match formats. T10 shows the greatest variation in the data, while T20 has a relatively more homogeneous distribution. This difference indicates a variation in performance characteristics between match formats before further inferential testing is conducted.

Assumption Test Results

Assumption tests were conducted to evaluate model suitability prior to the Linear Mixed Model analysis. The results of the residual normality test showed a p-value of 0.06, while visual inspection through Q–Q plots and residual plots was used to evaluate the distribution pattern and homogeneity of residual variance.

14
18

Table 5. Residual Normality

Variable	p
Residuals	0.06

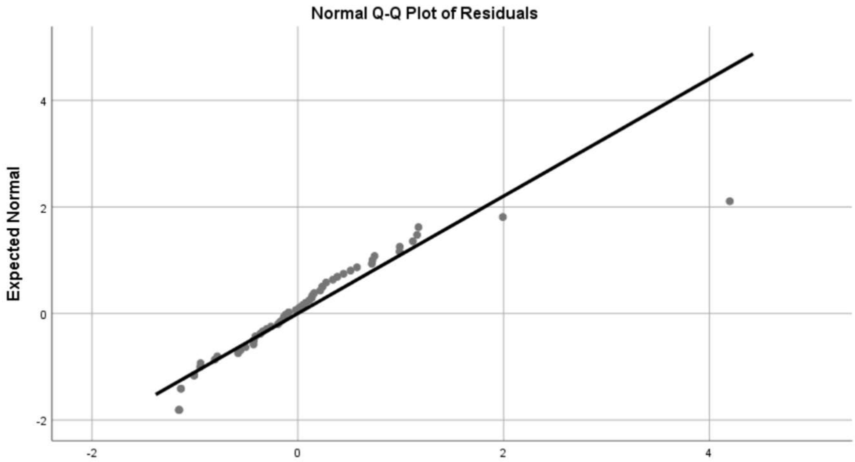

Figure 3. Q-Q Plot for Residuals

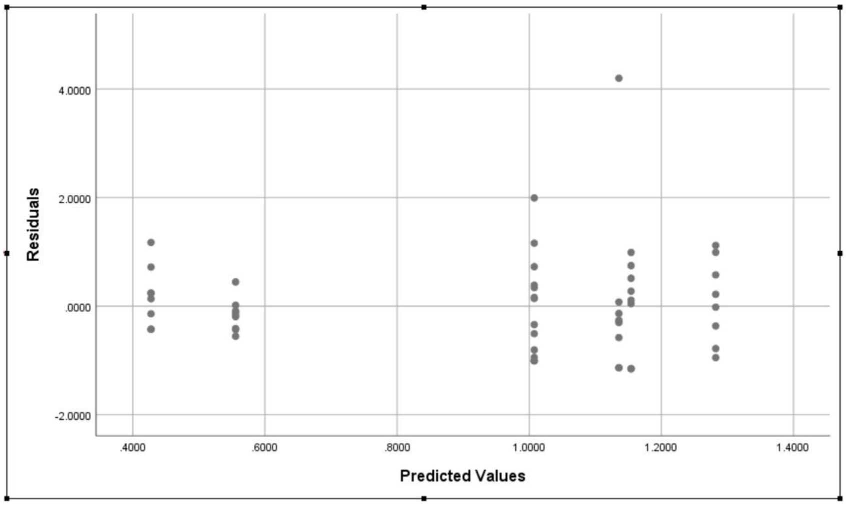

Figure 4. Homoscedasticity Test

P-value >0.05 indicates that the residuals meet the normality assumption. Furthermore, the dot pattern in the Q–Q plot follows the diagonal line, and the residual distribution does not form a systematic pattern, indicating that the homoscedasticity assumption is generally met for further analysis.

Main Model Results

10 A Linear Mixed Model was used to evaluate the effect of match type and inning on the observed variables. The results showed that match type had an F value of 2.91 (p=0.063), while inning had an F value of 0.255 (p=0.616).

Table 6. Main Model Results

Fixed Effect	df1	df2	F	p
Match Type	2	52	2.91	0.063
Inning	1	52	0.255	0.616

No significant effect of match type or innings was found on the analyzed variables (p>0.05). Although match type showed values approaching the significance threshold, these results indicate relatively consistent performance across match formats and phases of play.

Pairwise Comparison

Pairwise comparison analyses were performed to evaluate differences between innings and match types. Results showed that all comparisons had p values >0.05, including Inning 1 vs. Inning 2 (p=0.616), T10 vs. T20 (p=0.187), T10 vs. LMS (p=1.000), and T20 vs. LMS (p=0.083).

Table 7. Pairwise Comparasion

Comparasion	Mean Difference	SE	p	95% CI	
				Lower	Upper
Inning 1 vs Inning 2	−0.128	0.254	0.616	−0.637	0.381
T10 vs T20	0.580	0.304	0.187	−0.173	1.333
T10 vs LMS	−0.147	0.303	1.000	−0.895	0.602
T20 vs LMS	−0.727	0.321	0.083	−1.520	0.067

There were no significant differences across all pairs of groups compared. The 95% confidence interval crossing zero confirms that the observed mean differences do not yet represent a statistically significant effect.

Discussion

Research findings show that batting performance in cricket is influenced by many factors, including playing opportunities, scoring strategies, match situations, and individual player traits. The results also showed noticeable differences in player performance. Outfield scoring was the main method, and there were significant differences in the types of runs scored between the first and second halves. Following the ecological dynamics view, sports performance is seen as a system that develops through the interaction of the athlete, the task, and the competitive setting (Renshaw et al., 2022). Linear Mixed Model analysis indicated that match type and halves did not matter much once individual differences were considered. This supports the idea that performance is mostly shaped by individual dynamics and how players adapt to different contexts (Collins et al., 2025; Wood et al., 2023).

High variability in the distribution of balls and runs is a key finding of this study. The relatively large standard deviation compared to the mean indicates that hitting performance is not homogeneously distributed across observations. In competitive sports, performance variability does not necessarily reflect data instability but is a natural characteristic of complex adaptive systems. The constraints-led approach explains that athlete behavior develops through the dynamic interaction of individual constraints, the task, and the competition environment (Browne et al., 2021). Recent studies have also shown that fluctuations in elite athlete performance are an adaptive response to changing competition demands and situational dynamics during the match (Orth et al., 2017). Therefore, the performance heterogeneity in this study better represents the natural dynamics of competition rather than simply variation in statistical measurements.

The study found that 4-run and 6-run hits had a much bigger impact on the score than single hits. This implies that current batting strategies focus more on scoring through boundaries than on slowly building up scores through single hits. This change reflects the modern emphasis on a more aggressive style of play in cricket. In shorter formats, high-scoring, fast-paced cricket is important. Earlier research has also shown that scoring through boundaries has become more important due to changes in strategies and a rise in match intensity (Mullick, 2024).

From a tactical perspective, this approach can be interpreted through a risk-reward framework. The batter aims to maximize scoring opportunities while facing a greater risk of losing his wicket. In this study, we chose the categories 1, 4, and 6 runs. These are the most common ways to score and represent two main batting strategies in cricket. Players can build scores slowly through singles or score aggressively with boundary hits. The choice of these categories was based on their tactical importance and impact on the match score. The chi-square test showed a significant link between run type and innings of play. This indicates that the stage of play can affect how runs are scored. Although this relationship doesn't directly explain why it happens, the results suggest that changes in the match context can influence players' batting strategies and decision making.

Recent studies describe sports performance as a dynamic process. Athletes consistently adapt to factors such as competitive pressure, game tempo, and tactical demands throughout a match (Renshaw et al., 2022). An systems dynamics perspective explains that athletes modify their actions based on information from the game environment. This leads to different tactical responses at different competition stages (Davids et al., 2021). In cricket, recent research reveals the importance of situational variables and match context in forming players' decisions during play (Nair Ramanan et al., 2026). The differences in run-type distributions throughout innings likely reflect players' situational adaptations to changing match demands. This finding supports the idea that differences in performance are better understood as competitive adaptation instead than just statistical noise.

However, the effect sizes estimated with Cramer's V are relatively small. These data should be interpreted with caution. Statistical significance does not always mean an observed relationship has a strong or practical impact. Recent methodological literature indicates that larger sample sizes increase the chance of finding statistically significant relationships, even when the effect is small (Borg et al., 2023).

In sport and exercise science, depending exclusively on p-values has come under increasing criticism. This approach leads to simple interpretations of results, labeling them as "significant" or "insignificant" without considering the effect's practical magnitude (Swinton et al., 2022). Although this study found a statistical relationship between innings and run type, the practical contribution of this relationship to performance variation is likely limited. This interpretation helps avoid overstating the significance of data results. It follows current recommendations that emphasize effect size as a key part of interpreting sport research (Hilal Yagin et al., 2024).

An interesting finding emerged: the Chi-Square analysis showed a significant relationship, but the Linear Mixed Model (LMM) did not find a significant effect of round or match type. While these results may seem contradictory at first, they address different statistical perspectives. The Chi-Square test looks at overall relationships between frequency distributions. The LMM accounts for data structure and individual differences by including random effects (Brown, 2021).

Mixed-effects models are increasingly recommended in sports research. They capture the natural variability in athlete performance and handle data where observations are not independent. In this study, accounting for individual player variation made the match-stage effect no longer statistically significant. This suggests that observed differences are more probably driven by individual athlete characteristics than by match context. Overall, these results indicate that hitting performance is more strongly determined by individual player dynamics & tendencies than by match stage or conditions.

Although the match type effect did not reach significance (p=0.063), it approaches the statistical significance cutoff. It suggests a possible trend effect and still calls for careful interpretation. Modern statistical literature stresses that non-significant results should not be interpreted as evidence of the absence of an effect. Instead, they must be considered in the context of the study, sample size, group imbalance, and effect estimate (Matthews, 2021). Elite athletes in high-performance sport are known to have adaptive skills and self-regulatory behaviors. The non-significant result may reflect the athlete's ability to keep uniform performance across match formats. The imbalanced match distribution could also reduce the model's sensitivity to small effects.

Methodologically, the use of a Linear Mixed Model (LMM) is an important contribution of this study. Sports performance data typically has a hierarchical structure and repeated measurements for the same athlete. Using standard models that assume independent observations risks inaccurate estimates. Mixed-effects models are recommended within sports analytics because they take into account individual heterogeneity. They also preserve the natural structure of competition data (Brown, 2021). Including athlete random effects yields more realistic estimates and supports the need for multilevel models in sports performance analysis.

Overall, this study adds to sports performance analysis through an integrative approach. It examines the number of balls faced, runs scored, run type, innings, match type, and individual variation in a single framework. Many studies analyze performance indicators separately. In contrast, these outcomes show that cricket batting performance is complex yet influenced by playing opportunity, scoring efficiency, match situation, and individual player characteristics. This study considers on a single team, but total-event sampling supports maintaining the ecological validity of real match conditions. Future research ought to include factors such as opponent quality, situational match variables, and multilevel machine learning to provide a fuller understanding of performance in modern cricket.

Conclusions

This study shows that intermediate-level cricketers in Malang City have a varied distribution of runs scored among players, with some relying on single runs (1 run) and others more heavily on boundary hits (4 and 6 runs). Chi-square and t-test analyses found no significant differences between innings, indicating consistent player performance despite the evolving competitive environment. The variation in playing styles reflects a process of strategic exploration at the intermediate stage. These findings provide a basis for designing training programs that balance run accumulation and boundary hitting skills, and support tactical strategy development and community cricket development in developing areas.

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Conflict of interest

All authors declare no conflict of interest in this article.

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