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Role of Cricket Grounds in the Selection of T-20 Cricket Team

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***Abstract*:** This study delves into the intricate relationships that exist between T-20I cricket match spot conditions, team lineups, batting and bowling performances. We may fully comprehend the dynamics of the sport by closely examining four crucial latent factors: ground effect, team combination, bowling performance, and striking performance. We carry out extensive reliability assessments on the observed variables to guarantee the consistency and dependability of our data. To verify the applicability of our model, sophisticated statistical methods such as chi-square goodness of fit tests and multiple fit indices are utilized. Using the AMOS program, the structural equation model provides insightful information about how cricket performance is impacted by ground conditions. The results clearly show that playing conditions have an enormous effect on team combinations, which in turn influences team strategies. The investigation clearly shows that ground conditions do have an impact on individual batting and bowling performances, but they are not the main factors. This research has important managerial and coaching implications for cricket, since it offers valuable information for improving team tactics, player choices, and in-game adjustments. Understanding how the ground conditions interact with other factors might give an advantage over competitors, even though they are not the only element influencing individual performances.

Key Words: Cricket grounds, T-20 Cricket, ICC, ODI

1.Introduction

Comprehending and interpreting the world requires knowledge of statistics, an indispensable field of mathematics. In order to help us find patterns and make evidence-based decisions, it uses a variety of approaches for gathering, organizing, analyzing, and presenting data. Predictions and hypothesis testing are made easier by the statistical techniques that allow us to extrapolate valid conclusions from samples to bigger populations. The uncertainty, variability, and randomness that are present in many real-world occurrences are better understood because to this subject. Statistics enable professionals and researchers in a variety of domains, including the social sciences, economics, medicine, and engineering, to get knowledge and make defensible decisions [1]. Statistics are essential in sports, especially cricket, for assessing individual performance, examining team dynamics, and formulating game plans. Teams can forecast results and make strategic preparations by analyzing past match data and performance indicators; this illustrates the broad use of statistical methods in comprehending player performance and match dynamics [2-4].

Originally the classic summer sport in England, cricket has spread over the world and gained ardent supporters in Australia, India, Pakistan, the West Indies, and the British Isles. Known as the "gentleman's game," cricket has a long history that dates back to southeast England in the late 16th century. In the 18th century, it was declared the national sport of England. Throughout the 19th and 20th centuries, its impact expanded on a global scale. Featuring 50-over One-Day International (ODI) matches, the ICC Cricket World Cup has become one of the most prestigious and watched sporting events in the world. Concurrently, the Indian Premier competition (IPL) has become the premier cricket competition in the world, popularizing a dynamic 20-over format and encapsulating the excitement of contemporary cricket. Cricket's appeal is increased by its natural unpredictability and the application of complex probability models to predict results [5]. Three main formats exist for the sport: Twenty20 (T20) matches are the shortest and consist of 20 over’s per team. They are known for their fast-paced, high-scoring nature; Test matches, which last five days and involve two innings per team with a red ball and white clothing; and ODIs, which consist of 50 over’s per team with colored attire and a white ball.

Twenty20 Cup quickly became popular, and Australia and New Zealand played their first international Twenty20 match in 2005. The Indian Premier League (IPL), which debuted in 2008 and revolutionized the format with a hugely lucrative domestic league, following the ICC World Twenty20 in 2007. Other nations created their own leagues, like the Caribbean Premier League (CPL) and Australia's Big Bash League (BBL). The aggressive play style of Twenty20 cricket, which prioritizes big smashes and rapid scoring, has had a substantial impact on the sport, drawing in a new audience and boosting cricket's commercial viability. This format has also encouraged a more proactive approach in Test and ODI cricket strategies. The distinct qualities of cricket grounds, such as pitch conditions, outfield size, and climate, have a big impact on the choice of T20 teams. Every ground has unique difficulties that affect how players perform and approach. Teams are frequently selected with an eye toward how the pitch is expected to behave as well as other environmental considerations, highlighting the necessity of a variety of skills to take advantage of opportunities and outwit opponents. In addition, selectors play a critical role in resolving human error in conventional selection procedures and striking a balance in team composition. Software and automated solutions are being developed to improve the process of choosing teams by assessing players according to objective standards. The finest players are picked for particular situations according to this contemporary method of team selection, which adds to T20 cricket's dynamic character. Cricket's versatility and the strategic challenges of building a winning squad are highlighted by the ground's influence in team selection [5-9].

Integer programming techniques were created by GD Sharp and WJ Brettenny to rank cricket players according to runs scored and wickets taken, hence optimizing team compositions [10]. Using data from the 2011 Indian Premier League (IPL), Gholam R. Amin and Sujeet Kumar Sharma employed data envelopment analysis (DEA) to rank players according to a variety of parameters in order to objectively build the best teams [11]. In order to ensure that many criteria were taken into consideration when evaluating players in difficult circumstances, Kamble A.G. used the Analytical Hierarchy Process (AHP) [12]. Using data from the 2003 World Cup, Barr and Kantor combined strike rate and dismissal probability in a graphical technique to better measure one-day batting performance (Barr & Kantor, 2004). In order to create a 15-player side from 32 South African players for ODI matches, Gerber and Sharp used integer programming [13]. In order to evaluate T20 cricket performance, Prakash and Verma developed the Deep Player Performance Index (DPPI) utilizing Random Forest and K-Means clustering algorithms [14]. In their assessment of the technical, mental, physiological, and physical elements of fielding in cricket, MacDonald et al. underlined the importance of the skill [15].

In their analysis of T20 performance measures, [16] emphasized the significance of runs from boundary shots and wickets taken in the final six overs. Dot balls, total wickets, and run rate were determined by Irvine and Kennedy to be essential for T20 success [17]. To rank IPL 2019 players based on performance and auction prices, [18] used Structural Equation Modeling (SEM) and DEA. To maximize batting aggression in the second innings, Davis, Perera, and Swartz created a T20 match simulator [19]. Using random forest analysis [20] measured the effects of fielding with "expected runs saved due to fielding.

To rank T20 batsmen, [11] employed an Ordered Weighted Averaging (OWA) operator. In English domestic T20 cricket, [21] identified critical success indicators and recommended balanced bowling techniques. In order to overcome notable discrepancies in score patterns, [22] suggested an alternative to the Duckworth-Lewis technique for T20 matches.

To support strategic decision-making, [23] employed multiple linear regression and decision trees to forecast the results of T20 matches. [24] Used phase-based analysis of in-game variables to highlight the significance of timely strategic decisions in Twenty20 cricket. Using data from the 2007 T20 World Cup, [10] used integer-based models to quantify players' skills in getting wickets and scoring runs. Using DEA and SEM, [25] evaluated the IPL 2019 team's effectiveness.

[26] Used team strengths and dynamic game progressions to forecast IPL match winners in the second innings. To overcome measurement errors in their analysis of experimental data, [27] employed structural equation modeling (SEM). In order to help selectors, coaches, and players optimize plans and selections based on certain ground

qualities, the study on the function of cricket grounds in T20 team selection seeks to offer insights into how playing circumstances affect team performance. The goals are to evaluate how ground features affect bowling and batting performance as well as the relationship between ground impacts and team composition.

2. Methodology

2.1 Source and Data

Data on T-20 international cricket matches, grounds, and players will be gathered from the official websites of [28] in order to produce the study's findings. The main components of the data will be player performance indicators across various fields, including averages for bowling and hitting, runs scored, wickets claimed, and the quantity of games played at particular fields.

2.2 Data Processing

The dataset underwent thorough analysis using IBM SPSS Statistics software following the entry of the data from ESPNcricinfo. Examined, arranged, summed up, and evaluated in compliance with the study goals were all pertinent features found in the dataset.

2.3 Statistical Analysis

Using frequencies and percentages to emphasize the study variables' qualities, we conducted a descriptive statistical analysis of them. Teams and match results were examined using odds ratio and chi-square tests to investigate the relationship between dependent outcomes and explanatory variables. As part of our analytical approach, we also used Structural Equation Modeling (SEM).

2.4Structural Equation Modeling (SEM) and Path Diagram

Structural Equation Modeling (SEM) is used to analyze the relationships between observable variables (indicators) and latent variables (factors) using SPSS AMOS software [29]. Confirmatory factor analysis, which assesses latent variables, and path analysis, which analyzes correlations between dependent and independent variables using techniques like factor analysis, regression analysis, discriminant analysis, and canonical correlation, are combined in structural equation modeling (SEM) [30]. By combining ideas from conventional statistical methods like correlation, multiple regression, and analysis of variance, this strong multivariate approach makes hypothesis testing easier and enables the investigation of complicated variable interactions [31]. Statistical hypothesis testing is made possible by SEM, which uses measurement equations to analyze associations between latent variables and their indicators and structural equations to assess potential link agesbetween latent variable [32]. Path diagrams, also known as structural equation models (SEMs), visually represent the relationships between observed and latent variables. These diagrams use arrows to depict causal relationships, showing how variables are hypothesized to affect one another.

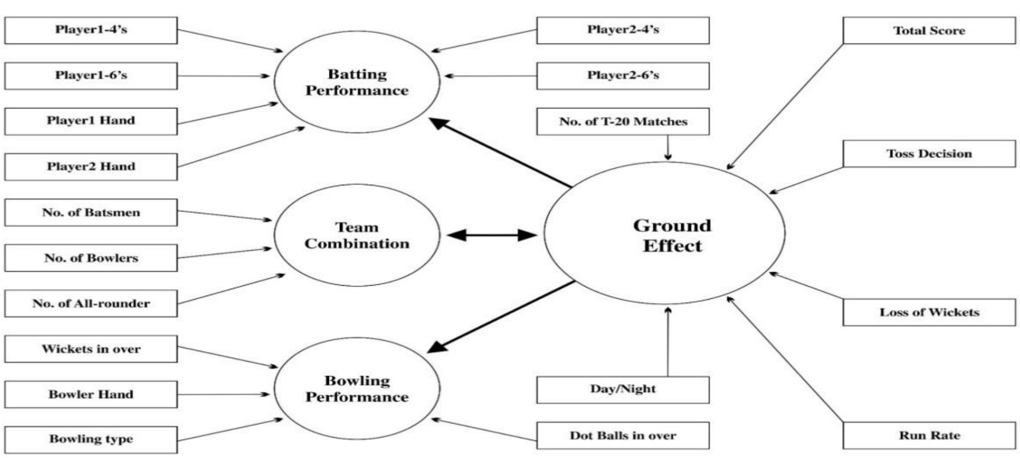


Fig 1: Path Diagram

2.5Chi Square Test

The chi-square test is a statistical tool used to evaluate the compatibility between collected data and a theoretical

model, applicable in fields like statistics, social sciences, and epidemiology. Introduced by Karl Pearson in the early 1900s, it serves both as a "goodness-of-fit" test for single-dimensional data and as a tool for contingency table analysis across multiple dimensions [33]. In Structural Equation Modeling (SEM), the chi-square test assesses model fit by comparing the actual covariance matrix with the one implied by the model.
The hypothesis in bivariate analysis can be formulated as:

2.6 Hypothesis

Hypothesis Null (H_1): The theoretical model involving the latent factors—ground effect, team combination, bowling performance, and striking performance—fits the observed data on T-20I cricket match conditions, team lineups, batting, and bowling performances.

Alternative hypothesis (H_0): The theoretical model involving the latent factors—ground effect, team combination, bowling performance, and striking performance—does not fit the observed data on T-20I cricket match circumstances, lineups, batting, and bowling performances.
The Chi-square test statistic can be defined as:

$$\chi 2 = \sum_{i=1}^{c} \sum_{j=1}^{r} \frac{(Oij - Eij)^2}{Eij}, \qquad (1)$$

where Oij= The number of observations in the cell(i,j);i=1,2,3...,r,j=1,2,3,...,c;Eij:Expected cell values. The test statistic follows a Chi-squared distribution with $(r-1) * (c-1)$degrees of freedom. The p-value collected from this test is used to make the decision.

3. Results and Discussion

3.1 Univariate Analysis

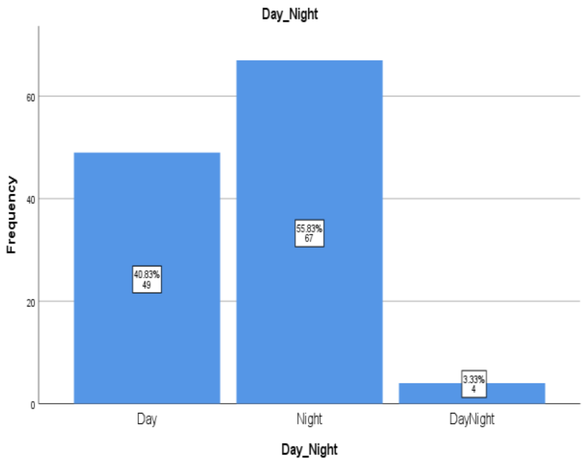
In this section, we evaluated the data using the most direct method of data analysis—looking at each variable separately. The reliability statistics of attributes and all observed variables,frequency distributions and matching percentages of our explanatory factors, along with the response, were displayed.

Table 1: Reliability statistics of attributes and all observed variables

S.No.	Attribute	No. of Items	Cronbach's Alpha	Remarks
1	Batting Performance	2	0.841	Reliable
2	Team Combination	3	0.927	Reliable
3	Bowling Performance	4	0.676	Acceptable
4	Ground Effect	4	0.973	Reliable

Table 2: Frequency Distribution of Day/Night Matches

Variable	Category	Frequency	Percent
Day/Night	Day	49	40.8
	Night	67	55.8
	Day/ Night	4	3.3
Toss Decision	Elected to Bat First	50	41.7
	Elected to Field First	70	58.3
Total		**120**	**100.0**



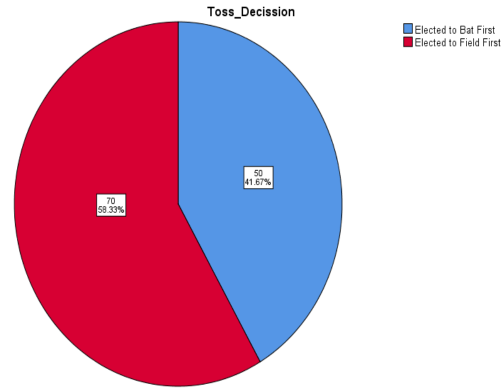
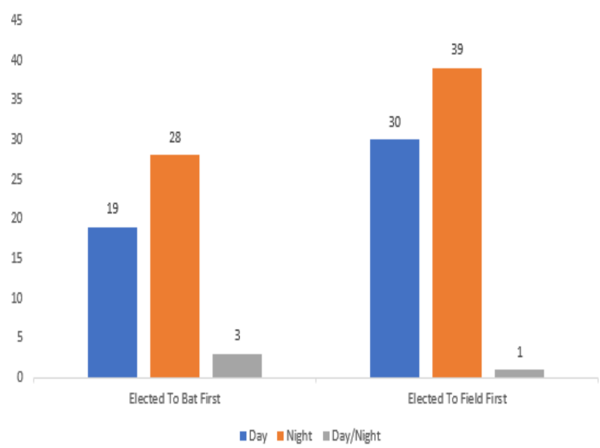


Figure 2 Figure 3

Table 3: Toss Decision by Day/Night and Winner Team

Toss Decision	**Day/Night - Day**	**Day/Night – Night**	**Day/Night - Day/Night**	**Total**
Elected to Bat First	19	28	3	50
Elected to Field First	30	39	1	70
Total	49	67	4	120
Toss Decision	**Winner Team - 1st Inning Team**	**Winner Team - 2nd Inning Team**	**Winner Team - Match Tied**	**Total**
Elected to Bat First	31	19	0	50
Elected to Field First	33	34	3	70
Total	64	53	3	120



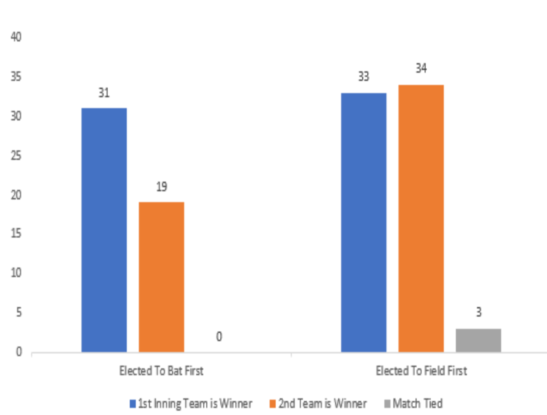


Figure 4 Figure 5

The above table, table 1,presents the reliability statistics for the attributes examined in this study.Using Cronbach's Alpha, reliability analysis evaluates the coherence of four underlying variables and 13 measured variables in the model, table 2 and table 3 shows that the data on Day/Night matches shows that most games were played at night

(55.8%), followed by day (40.8%), and day/night (3.3%). Regarding the toss decision, teams elected to field first more frequently (58.3%) compared to batting first (41.7%). When examining toss decisions relative to match times, teams choosing to field first did so mostly at night (39), while teams choosing to bat first did so primarily during the day (19). In terms of match outcomes, teams electing to bat first won more often in the first innings (31), while teams electing to field first had a more balanced outcome, winning 33 times in the first innings and 34 times in the second innings. The data suggests that the toss decision has a notable impact on match strategy and outcomes, influenced by the time of day and the innings in which the team plays.

3.2 Bivariate analysis

The relationship between team combination and ground effect, batting performance, and bowling performance was investigated in this section using a bivariate approach. First, the four components of the measurement model—which is assessed by observable variables—are fitted using Confirmatory Factor Analysis (CFA) and AMOS software. The chi-square goodness of fit test is used to evaluate the model's fit after it has been identified to ascertain sample moments and parameters. The model's fit is then further confirmed using additional metrics such the TLI, IFI, RMSEA, NFI, and CFI.

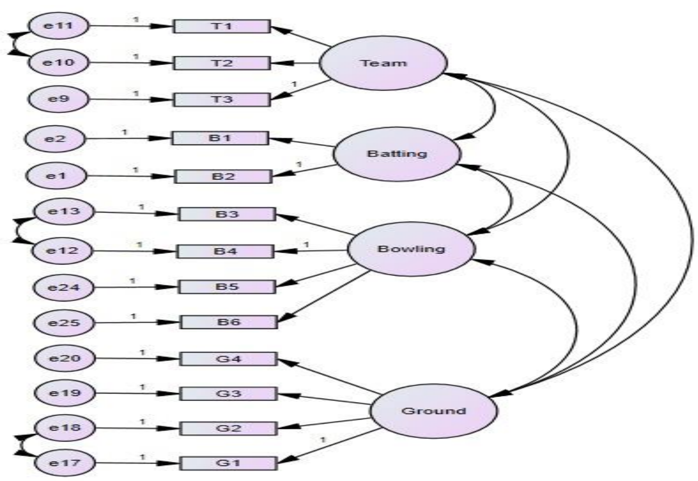


Figure 6: TheMeasurement Model

Table 4: Model Identification and Goodness-of-Fit Statistics

Notation	Value	Description
M	104	Number of Distinct Sample Moments
K	48	Number of Parameters to be Estimated
d.f	56	Degrees of Freedom (d.f = M - K)
Fit Statistic	**Statistic Value**	**Recommended Value**
X2	186.636	
d.f	56	
Significance	0.000 < 0.05	
X2/d.f	3.333	< 5
Fit Statistic	**Statistic Value**	**Recommended Value**
NFI	0.982	Close to 1
CFI	0.987	Close to 1

TLI	0.980	Close to 1
IFI	0.988	Close to 1
RFI	0.971	Close to 1
Fit Statistic	**Statistic Value**	**Recommended Value**
RMSEA	0.057	Close to 0

The above model identification table indicates that there are 56 degrees of freedom with 104 different sample moments and 48 estimated parameters. The relative chi-square (X^2/d.f.) is 3.333, suggesting a reasonable fit as it is below the threshold of 5, and the chi-square value (X^2) is 186.636 with a significance level of 0.000. NFI (0.982), CFI (0.987), TLI (0.980), IFI (0.988), and RFI (0.971) are a numerous more goodness-of-fit indices that are near to 1, indicating a good model fit. The model's adequacy is further supported by the RMSEA value of 0.057, which is quite near to 0.

3.3 Entire Structural Model

The entire structural model incorporates measurement errors and immediate relationships throughout constructs for a robust analysis, thoroughly assessing the relationship between numerous concepts and their measurement indicators.

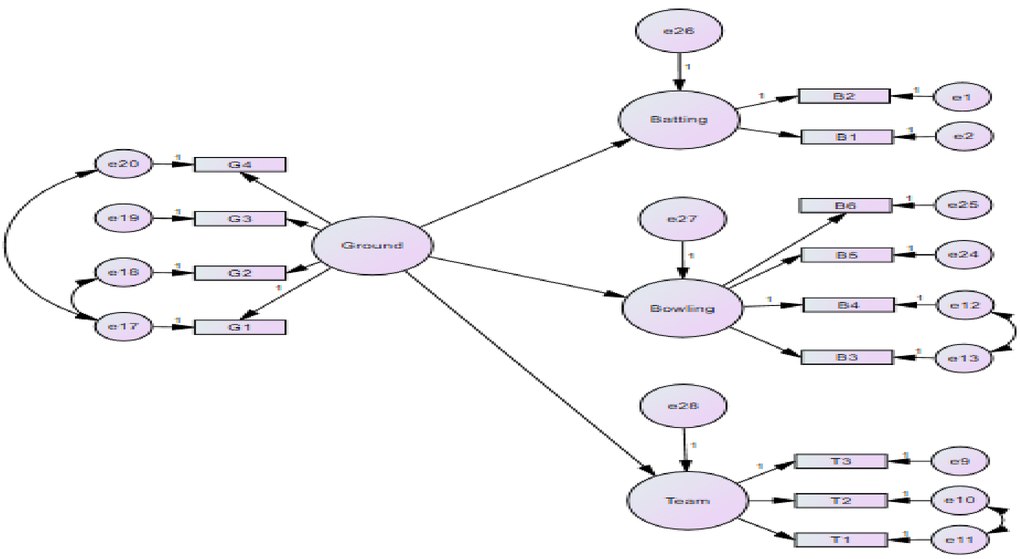


Figure 7: Structural Equation Model for Ground Effect on Batting, Bowling, and Team Performance

Table 5: Model Identification and Goodness-of-Fit Statistics

Notation	Value	Description
M	104	Number of Distinct Sample Moments
K	46	Number of Parameters to be estimated
d.f=M-K	58	Degree of Freedom
Fit Statistic	**Statistic Value**	**Recommended Value**
X^2	265.475	
d.f	58	
Significance	0.000	<0.05
X^2/d.f	4.577	< 5
Fit Statistic	**Statistic Value**	**Recommended Value**
Fit Statistic	Statistic Value	Close to 1

NFI	0.975	Close to 1
CFI	0.980	Close to 1
TLI	0.969	Close to 1
IFI	0.980	Close to 1
Fit Statistic	**Statistic Value**	**Recommended Value**
RMSEA	0.070	Close to 0

The model identification table shows 46 parameters to be estimated and 104 distinct sample moments, yielding 58 degrees of freedom. The chi-square goodness of fit test yields a value of 265.475 at a significance level of 0.000, and an X^2/d.f ratio of 4.577, indicating a satisfactory model fit. Other fit indices, including NFI (0.975), CFI (0.980), TLI (0.969), and IFI (0.980), all close to 1, and an RMSEA value of 0.070, examine the model's sufficiency.

4. Conclusion

In this study, we investigated the complex interactions between cricket match variables such as ground conditions, team makeup, batting and bowling performances. Our results, which are backed by a thorough reliability study of the data gathered, show the intricate dynamics at work in this activity. We clarified the interaction of four latent factors—Batting Performance, Bowling Performance, Team Combination, and Ground Effect—by carefully analyzing each one. The model's strong fit was validated by various statistical measures and indices, such as the Tucker Lewis index, relative fit index, comparative fit index, normed fit indices, and chi-square goodness of fit test, incremental fit index, and relative fit index. The accuracy of the model was verified by low RMSEA values. We learned more about how cricket performance is affected by ground conditions by using AMOS for structural equation modeling. Specifically, we found a strong positive relationship between ground conditions and team makeup. The study did discover that individual batting and bowling performances were statistically not affected by ground conditions, indicating that other factors may be more important in these areas of play.

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