DEVELOPING A PREDICTIVE MODEL FOR THE FRONT-FOOT COVER DRIVE AMONG MPCA FEMALE CRICKETERS BASED ON SELECTED ANTHROPOMETRIC VARIABLES

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Abstract: The front-foot cover drive is a technically demanding cricket stroke requiring precise footwork, balance, and bat-speed control. This study developed a regression model to predict cover-drive performance from selected anthropometric variables in state-level female cricketers. Twenty MPCA-affiliated female cricketers (mean age 21.3 ± 2.1 years) participated. Five anthropometric variables — stature, arm length, leg length, biacromial breadth, and BMI — were measured following ISAK protocols. Each participant executed five front-foot cover drives against a standardised bowling-machine delivery, scored by three BCCI-certified coaches (1–10 scale). After verifying assumptions, stepwise multiple linear regression identified arm length ($\beta = 0.41$, $p < 0.01$), leg length ($\beta = 0.33$, $p < 0.05$), and BMI ($\beta = -0.38$, $p < 0.05$) as significant predictors. The model explained 72% of variance ($R^2 = 0.72$, Adjusted $R^2 = 0.65$, $F = 11.32$, $p < 0.001$). Limb-segment proportions — not overall size — drive cover-drive proficiency.

Keywords: **Anthropometry, cover drive, female cricketers, regression model, talent identification, BMI**

INTRODUCTION

Cricket batting is a perceptuo-motor skill in which biomechanical efficiency and segmental anthropometry jointly determine stroke quality (Patel & Kumar, 2021). Among classical driving shots, the front-foot cover drive demands forward weight transfer, a stable base, and a fully extended bat path through the line of the ball. Yet sport-science research has focused on fast-bowling workloads and generic fitness profiles rather than stroke-specific anthropometric determinants (Brazier et al., 2024; Singh, 2019).

The literature on female cricketers remains particularly sparse. Most reference data pertain to male fast bowlers (Stuelcken et al., 2007) or pooled skill groups; strikingly, no published regression equation predicts a specific batting stroke from anthropometric inputs in a women's cohort (KUMAR, 2022; Mandoli et al., 2021; Singh, 2024). As a result, talent identification in Indian women's cricket relies on subjective match observation rather than measurable screening criteria.

This study addressed that gap by: (a) examining relationships between selected anthropometric variables and cover-drive performance in MPCA female cricketers, (b) developing a predictive regression model, and (c) evaluating its applicability for selection. It was hypothesised that arm length and leg length would positively predict performance while BMI would contribute negatively.

LITERATURE REVIEW

2.1 Anthropometric Profiling in Cricket

Kinanthropometric profiling has been widely adopted in cricket for talent identification and position classification. Stuelcken et al. established reference data for elite fast bowlers, showing segment lengths and somatotype categories differ meaningfully across playing roles and sexes (Stuelcken et al., 2007). Recent work on female cricketers confirmed that stature and body mass vary significantly by standard and position, with seam bowlers taller and heavier than non-seam players (Brazier et al., 2024). For Indian female cricketers specifically, discriminant functions using muscle mass, fat percentage, shoulder diameter, and arm length have achieved 67–80% correct role classification (Mandoli et al., 2021; Singh, 2024) — confirming the discriminative value of anthropometry in women's cricket.

2.2 Anthropometry and Batting Performance

In baseball — a bat-sport analogue — anthropometric variables explained 29–55% of variance in contact and hard-hit outcomes, while body-fat percentage was a strong negative predictor of slugging (Kohn et al., 2024; Vinod et al., 2018). In cricket, a stepwise regression on 25 male state-level players identified age, chest skinfold, and thigh skinfold as key predictors, underscoring the role of body composition alongside linear dimensions (KUMAR, 2022). Multivariate analysis on U-16 district players found that motor variables contributed modestly, supporting the view that anthropometric factors cannot be overlooked even when reaction-based predictors are added (Kumar & Kumar, 2025).

2.3 Biomechanical Rationale

Biomechanically, the cover drive requires maximal forward reach, stable head–knee–toe alignment at front-foot contact, and an extended arm–bat lever. Longer arms provide reach without overstriding; longer legs extend stride length and lower the centre of mass; lower BMI favours quicker repositioning and trunk rotation (Patel & Kumar, 2021; Vinod et al., 2018). These premises underpin the directional hypotheses tested here.

METHODOLOGY

3.1 Participants

Twenty state-level MPCA female cricketers volunteered (mean age 21.3 ± 2.1 years). Sample size was determined a priori using G*Power 3.1 for multiple regression with five predictors, medium effect size ($f^2 = 0.35$), $\alpha = 0.05$, and power = 0.80, yielding N = 20.

Inclusion criteria: ≥ 2 consecutive MPCA seasons of registration; age 18–25; no injury in the past six months. **Exclusion criteria:** prior limb surgery; pregnancy/postpartum (< 6 months).

3.2 Anthropometric Measurements

All measurements were conducted by an ISAK Level-3 accredited anthropometrist using calibrated instruments (Marfell-Jones et al., 2006; Silva & Vieira, 2020), following ISAK landmarks and positioning (Bryan et al., 2021; Paulose-Ram et al., 2021):

- **Stature (cm):** portable stadiometer, Frankfort plane aligned.
- **Arm length (cm):** acromiale to dactylion.
- **Leg length (cm):** ASIS to medial malleolus, supine.
- **Biacromial breadth (cm):** broad-blade sliding caliper.
- **Body mass (kg).**
- **BMI (kg/m²):** body mass ÷ stature².

Test–retest reliability on 10 participants yielded ICC > 0.97 for all variables.

3.3 Performance Evaluation

After a standardised warm-up, each participant executed five front-foot cover drives to balls bowled by a calibrated BOLA® bowling machine (length 5–6 m, pace ~80 km/h, leg-stump line). Shots were filmed at 50 fps perpendicular to the batting plane. Three BCCI-certified coaches, blinded to identity, rated each shot on a 1–10 technical-execution scale. Inter-rater reliability was high (ICC = 0.91; Cronbach's $\alpha = 0.89$).

3.4 Statistical Analysis

Data were processed in SPSS v28. Assumption testing preceded all inferential analyses: normality (Shapiro–Wilk), linearity (scatterplots), homoscedasticity (Breusch–Pagan), multicollinearity (VIF < 5), and independence of residuals (Durbin–Watson). Pearson correlation (Bonferroni-adjusted $\alpha = 0.01$) and stepwise multiple linear regression (entry $p < 0.05$; removal $p > 0.10$) were applied. Effect size (f^2) and 95% CIs were reported.

RESULTS

4.1 Descriptive Statistics

Table 1
Descriptive profile of the Subject

Variable	Mean ± SD	Range
Age (years)	21.3 ± 2.1	18–25
Stature (cm)	162.4 ± 5.8	152–172
Arm Length (cm)	71.6 ± 3.2	66–78
Leg Length (cm)	85.3 ± 4.1	78–92
Biacromial Breadth (cm)	37.8 ± 2.9	33–43
BMI (kg/m²)	21.9 ± 2.1	18.4–26.2
Cover-Drive Score (1–10)	7.4 ± 0.9	5.6–8.8

4.2 Assumption Testing

All assumptions were met: Shapiro–Wilk $p > 0.05$; Breusch–Pagan $p = 0.21$; VIF 1.18–2.43; Durbin–Watson = 1.92.

4.3 Correlation Analysis

Table 2
Pearson correlations with cover-drive score

Variable	r	p
Arm Length	0.68	< 0.001**
Leg Length	0.60	0.005*
BMI	–0.52	0.019*
Stature	0.33	0.151
Biacromial Breadth	0.28	0.224

*p < 0.05; **p < 0.001 (Bonferroni-adjusted $\alpha = 0.01$)

4.4 Regression Model

Table 3
Stepwise regression output

Predictor	B	SE	β	t	p	95% CI
Constant	1.12	1.04	—	1.08	0.299	[–1.06, 3.30]
Arm Length	0.23	0.07	0.41	3.29	0.005	[0.08, 0.38]
Leg Length	0.19	0.08	0.33	2.37	0.031	[0.02, 0.36]
BMI	–0.35	0.13	–0.38	–2.69	0.016	[–0.62, –0.08]

Model: *$R^2 = 0.72$, Adjusted $R^2 = 0.65$, SEE = 0.54, $F = 11.32$, $p < 0.001$, $f^2 = 2.57$.*

Regression Equation:

$$\text{Cover-Drive Score} = 1.12 + 0.23(\text{Arm Length}) + 0.19(\text{Leg Length}) - 0.35(\text{BMI})$$

DISCUSSION

★ **Arm length was the dominant positive predictor (β = 0.41).** A longer distal lever enables full bat extension at impact without overstriding — consistent with discriminant literature that identifies arm length as a key anatomical discriminator between female batting and bowling roles (Mandoli et al., 2021; Singh, 2024).

★ **Leg length contributed positively (β = 0.33).** Longer true leg length extends stride geometry for the same angular displacement, enabling forward press without compromising base stability, in line with position-specific anthropometric norms in female cricket (Brazier et al., 2024; Stuelcken et al., 2007).

★ **BMI made a significant negative contribution (β = –0.38).** This mirrors NCAA baseball evidence that higher fat mass depresses bat-speed-dependent outcomes (Vinod et al., 2018), likely reflecting quicker trunk rotation, faster foot repositioning, and reduced joint loading at front-foot impact.

★ **Stature and biacromial breadth were non-significant.** Cover-drive execution depends less on absolute size than on **segmental proportionality** — a finding consistent with talent-identification literature emphasising lever ratios over stature (Stuelcken et al., 2007).

★ **Variance explained (72%) exceeds prior anthropometric-batting studies** (4–55% in baseball (Kohn et al., 2024; Vinod et al., 2018); 2.1% for motor predictors alone in district cricket (Kumar & Kumar, 2025)). The likely reasons are stroke-specific operationalisation of the outcome, the homogeneous skill profile of state-level players, and the focus on segment lengths rather than aggregate size.

CONCLUSION

Selected anthropometric variables explain 72% of the variance in front-foot cover-drive performance among MPCA female cricketers. Arm length and leg length contribute positively; BMI contributes negatively. The model offers a field-applicable screening tool for talent identification and selection. Multi-state replication with body-composition partitioning remains the next step.

AUTHOR CONTRIBUTIONS

S.K. conceptualised the study, collected data, and performed analysis. S.Y. supervised methodology and statistical analysis. R.K. contributed to literature review and manuscript drafting. All authors read and approved the final manuscript.

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