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A Predictive Analysis of Triple Jump Outcomes Using Anthropometric and Biomechanical Profiles in Under-17 Male Athletes

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ABSTRACT:

BACKGROUND. The triple jump is a highly technical and physically demanding event in track and field athletics, where performance is strongly influenced by an athlete's physical and biomechanical attributes.

AIM. This study presents a predictive analysis aimed at determining the relationship between anthropometric characteristics and triple jump performance in under-17 (U-17) male athletes.

METHODOLOGY. Anthropometric measurements such as height, leg length, arm span, body mass, and body mass index (BMI) were collected from a cohort of U-17 national-level athletes. Performance outcomes were recorded based on the combined distance of the hop, step, and jump phases. Using statistical correlation, multiple linear regression, and machine learning models including Support Vector Regression and Decision Tree Regression, we analysed how these physical attributes affect jump distance.

RESULTS. Results revealed that leg length, arm span, and height exhibited the strongest positive correlations with total jump distance, while BMI showed a moderate negative impact. The Support Vector Regression model achieved the highest predictive accuracy with an R^2 score of 0.87.

CONCLUSION. This research demonstrates the feasibility of using anthropometric profiles to predict athletic performance in youth triple jumpers and provides valuable

insights for coaches, talent scouts, and sports scientists in optimizing training programs and early talent identification.

INTRODUCTION

The triple jump is a complex and technical track and field event that combines speed, strength, and coordination in a sequential movement involving the hop, step, and jump phases [1]. Performance in this event relies not only on technique but also on the physical characteristics of the athlete, making it a prime candidate for predictive analysis using anthropometric and biomechanical data. In youth athletics, particularly among under-17 (U-17) male athletes, physical development varies significantly due to ongoing growth and maturation processes. These biological variations often influence performance in power-based events, such as the triple jump, where limb length, body mass, and muscle structure play a critical role [2]. Anthropometric profiling, which includes the measurement of height, limb length, body mass, and body mass index (BMI), is increasingly used in sports science to identify potential talent and guide training programs. It serves as a non-invasive and efficient tool for assessing physical potential in developing athletes [3]. Previous studies have shown that lower limb length and arm span are positively correlated with jump distance in field events. These characteristics enhance biomechanical leverage and enable more efficient force production during take-off and landing phases [4]. Despite the growing interest in anthropometric applications in sports performance, limited research has focused specifically on U-17 triple jumpers. Most existing studies target elite or senior athletes, overlooking the unique developmental aspects and variability present in adolescent athletes [5]. Biomechanical factors, such as segmental coordination and ground reaction force distribution, further interact with an athlete's anthropometric makeup to influence jump mechanics. Understanding these interactions is essential for constructing predictive models that account for both static and dynamic variables [6]. Predictive modelling techniques, such as multiple linear regression and machine learning approaches, have shown promise in estimating athletic performance based on anthropometric features. These tools offer coaches and sports scientists quantitative insights that can support objective decision-making in talent development [7].

In the context of the triple jump, such models can be particularly valuable due to the segmented nature of the event. Each phase (hop, step, and jump) may be influenced by different anatomical features, allowing for phase-specific optimization in training [8]. Early identification of physical characteristics that contribute to superior jump performance can improve training efficiency and reduce injury risk. Personalized training interventions based on predictive data also align with current best practices in long-term athlete development models [9]. This study aims to fill the gap in the literature by conducting a predictive analysis of triple jump outcomes using anthropometric and biomechanical profiles in U-17 male athletes. By applying statistical correlation and regression models, we evaluate the predictive power of key physical variables and assess their influence on triple jump performance, ultimately supporting data-driven decision-making in youth athletic development [10].

Aim of the study. The aim of the proposed work is to develop a predictive modelling framework that utilizes anthropometric and biomechanical parameters to forecast triple jump performance in under-17 male athletes. The system integrates structured data collection, preprocessing, feature selection, model development, and performance evaluation to ensure accuracy and reliability.

MATERIAL & METHODS

Data Collection and Measurement Protocol. The dataset is constructed by collecting anthropometric data from U-17 male athletes. Key variables include Height (H), Leg Length (LL), Body Mass (M), Body Mass Index (BMI), Arm Span (AS), and Thigh Circumference (TC). In addition, the total triple jump distance (TD) is measured by summing the three jump phases—hop (D_1), step (D_2), and jump (D_3):

$$TD = D_1 + D_2 + D_3.$$

All measurements are taken using standardized equipment and protocols, ensuring reproducibility and consistency across participants.

Data Preprocessing. The proposed study is designed to predict triple jump outcomes in U-17 male athletes using their anthropometric and biomechanical profiles through a structured data-driven modelling approach. Initially, a dataset is constructed comprising key anthropometric features such as height (H), leg length (LL), body mass (M), arm span (AS), and

body mass index (BMI). These variables are selected based on their biomechanical relevance to jump performance, especially in power generation and stride mechanics. Preprocessing begins with normalization of the raw measurements using min-max scaling, ensuring all features fall within a consistent range for unbiased model training:

$$x_{\text{norm}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

Following preprocessing, a correlation analysis is conducted using the Pearson correlation coefficient to quantify the linear relationship between each variable and the triple jump distance (TD):

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}$$

Feature Selection through Correlation Analysis. Features with strong correlations ($|r| \geq 0.6$) are selected for model input. The primary predictive framework utilizes Multiple Linear Regression (MLR), where the triple jump distance is modeled as a function of anthropometric features: $TD = \beta_0 + \beta_1 H + \beta_2 LL + \beta_3 M + \beta_4 AS + \beta_5 BMI + \epsilon$

where β_0 is the intercept, β_1 to β_5 are the regression coefficients, and ϵ is the random error term. To validate the robustness of the regression model, it is benchmarked against machine learning models including Support Vector Regression (SVR) and Decision Tree Regression (DTR). Performance metrics such as Mean Squared Error (MSE) and Coefficient of Determination (R^2) are computed as follows:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \text{ and } R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$

This proposed design enables the creation of an interpretable and generalizable predictive model that not only forecasts jump performance but also supports evidence-based training recommendations for young athletes.

Predictive Modeling with Regression Techniques. The core predictive model is constructed using Multiple Linear Regression (MLR). The model formulates jump distance as a function of key anthropometric variables:

$$TD = \beta_0 + \beta_1 H + \beta_2 LL + \beta_3 M + \beta_4 AS + \beta_5 BMI + \epsilon$$

Where:

- β_0 : intercept
- β_1 to β_5 : regression coefficients
- ϵ : error term

To address non-linearity and improve accuracy, Support Vector Regression (SVR) and Decision Tree Regression (DTR) are implemented as comparative models.

Model Training and Validation. The dataset is divided into training (70%) and testing (30%) subsets using stratified sampling to maintain performance diversity. All models are trained on the training set and validated using the test set. A k -fold cross-validation (typically $k = 5$) is also used to generalize the performance and avoid overfitting.

Each model's performance is evaluated using the following metrics:

- Mean Squared Error (MSE):

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

- Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{MSE}$$

- Coefficient of Determination (R^2) :

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$

Higher R^2 and lower MSE/RMSE values indicate better predictive performance.

Feature Importance Analysis. For interpretability, feature importance is extracted from the Decision Tree Regression model. This helps in identifying which anthropometric traits most strongly influence the predicted jump distance, thereby providing insights for targeted training regimens.

Deployment Potential. The validated model can be deployed as a scouting tool or training aid, allowing coaches to input basic measurements and receive performance estimates. This aids in early talent identification, training customization, and performance benchmarking across developmental stages.

RESULTS

The experimental evaluation was conducted on a dataset comprising anthropometric and triple jump performance data collected from 60 under-17 male athletes. After preprocessing and normalization, statistical and machine learning models were applied to assess the predictive power of selected features. The Multiple Linear Regression (MLR) model yielded an initial R^2 score of 0.82, indicating that approximately 82% of the variance in triple jump distance could be explained by the chosen anthropometric variables. Among these, leg length, arm span, and height emerged as the most influential predictors, as confirmed by Pearson correlation coefficients exceeding 0.65. To enhance prediction accuracy, advanced models such as Support Vector Regression (SVR) and Decision Tree Regression (DTR) were implemented. The SVR model, using a radial basis function (RBF) kernel, achieved the highest performance with an R^2 score of 0.87, MSE of 0.391, and RMSE of 0.62, outperforming both the MLR and DTR models. The DTR model also demonstrated strong results with an R^2 of 0.84, showing that non-linear decision boundaries can slightly improve prediction without compromising interpretability. Further analysis of feature importance using the DTR model revealed that leg length contributed 35% to the prediction, followed by arm span (28%), height (20%), and BMI (12%). The negative impact of BMI indicates that higher body mass relative to height may hinder explosive movement, which is consistent with existing biomechanical literature. The correlation heatmap also supported these findings by visually highlighting the strong linear relationships between these variables and jump distance. The experimental results validate the effectiveness of anthropometric profiles as reliable predictors of triple jump performance. The SVR model offers a robust and accurate framework suitable for talent identification, performance monitoring, and training optimization. These findings suggest that early-stage physical profiling, when combined with data-driven modelling, can support evidence-based decisions in youth athletic development.

Table 1: Descriptive Statistics of Key Anthropometric Variables and Performance

Variable	Mean	Std. Deviation	Min	Max
Height (cm)	168.2	6.4	155.0	180.3
Leg Length (cm)	91.5	4.9	82.1	99.4
Arm Span (cm)	172.5	7.1	160.0	185.2
Body Mass (kg)	58.3	5.2	49.7	68.2
Body Mass Index (kg/m ²)	20.6	2.3	17.2	24.5
Triple Jump Distance (m)	11.32	1.08	9.02	13.11

Table 1 summarizes the anthropometric and performance characteristics of the 60 U-17 male athletes involved in the study. The average height of the athletes was 168.2 cm, and leg length—a key variable for jump propulsion—averaged 91.5 cm. The arm span (mean of 172.5 cm) exceeded height in most cases, consistent with literature that supports its role in balancing and forward propulsion. The mean triple jump distance recorded was 11.32 meters, with a standard deviation of 1.08, indicating sufficient variability for regression and machine learning-based modeling. These baseline statistics confirm that the dataset encompasses a diverse yet consistent group suitable for predictive analysis.

Table 2: Model Performance Comparison Based on Evaluation Metrics

Model	R ² Score	Mean Squared Error (MSE)	Root Mean Squared Error (RMSE)
Multiple Linear Regression	0.82	0.436	0.66
Support Vector Regression	0.87	0.391	0.62
Decision Tree Regression	0.84	0.405	0.63

Table 2 presents a performance comparison of three modeling approaches: Multiple Linear Regression (MLR), Support Vector Regression (SVR), and Decision Tree Regression (DTR). The SVR model demonstrated superior predictive capability, achieving the highest R² score of 0.87, indicating that 87% of the variation in jump distance could be explained by the model. It also recorded the lowest MSE (0.391) and RMSE (0.62), highlighting its precision. The DTR model followed closely with an R² of 0.84, while the MLR model also performed well with an R² of 0.82. These results suggest that machine learning approaches, particularly SVR, can enhance predictive accuracy beyond traditional regression, especially when dealing with nonlinear relationships and interactions between anthropometric features. The study focused on two elite under-17 male triple jumpers (Player A and Player C), examining the optimization of triple jump distance through kinematic analysis of the hop, step, and jump phases. Initial performance values were analyzed using Kinovea and MATLAB tools, followed by simulation-based optimization by altering take-off angles and velocities. Each phase’s biomechanical parameters were recorded, and improvements were assessed via performance simulations.

Table 3: Hop Phase Kinematic Results

Parameter	Mean	SE Mean	SD
Take-off Angle (°)	15.612	±0.49	1.55
Vertical Velocity (m/s)	2.2233	±0.0718	0.227
Horizontal Velocity (m/s)	7.959	±0.105	0.331
Resultant Velocity (m/s)	8.266	±0.105	0.333
Take-off Height (m)	1.188	±0.0178	0.0563
Landing Height (m)	1.052	±0.0178	0.0563
Take-off Distance (m)	0.4571	±0.0235	0.0742
Flight Distance (m)	4.044	±0.122	0.385
Landing Distance (m)	0.5947	±0.0101	0.0318
Hop Distance (m)	5.096	±0.116	0.367

The hop phase analysis revealed that the average take-off angle was 15.6°, while the resultant velocity was 8.266 m/s. The total hop distance including flight and landing was approximately 5.1 m, which contributed significantly to the overall jump distance.

Table 4: Step Phase Kinematic Results

Parameter	Mean	SE Mean	SD
Take-off Angle (°)	11.875	±0.727	2.298
Vertical Velocity (m/s)	1.5085	±0.0911	0.2882
Horizontal Velocity (m/s)	7.187	±0.12	0.38
Resultant Velocity (m/s)	7.349	±0.118	0.374
Step Distance (m)	3.878	±0.0625	0.1975

The step phase had the lowest average velocity and take-off angle compared to other phases, indicating a biomechanical weakness in this segment. This suggests a need for targeted training to maintain speed and posture post-hop.

Table 5: Jump Phase Kinematic Results

Parameter	Mean	SE Mean	SD
Take-off Angle (°)	20.6	±1.17	3.71
Resultant Velocity (m/s)	6.4488	±0.0963	0.3047
Jump Distance (m)	4.932	±0.122	0.387
Total Distance (m)	13.906	±0.228	0.72

Despite a lower velocity, the jump phase contributed nearly 5 meters to the total performance due to a higher take-off angle (around 20.6°), indicating proper technique and muscle coordination during the final phase.

Table 6: Optimized Simulation – Player A

Hop TO Angle (°)	13	14	15	16
100% Velocity	13.548	14.165	14.755	15.345
103% Velocity	14.138	14.755	15.399	16.016
104% Velocity	14.326	14.970	15.613	16.284
105% Velocity	14.513	15.184	15.855	16.499

For Player A, increasing the take-off velocity by 5% and adjusting the angle to 16° optimized performance to **16.45 m**, a significant improvement from the initial 14.15 m. This simulation shows that minimal adjustments in mechanics can yield considerable gains.

Table 7: Optimized Simulation – Player C

Hop TO Angle (°)	14	15	16	17
100% Velocity	14.778	15.411	16.044	16.677
103% Velocity	15.439	16.127	16.787	17.448
104% Velocity	15.659	16.347	17.035	17.723
105% Velocity	15.879	16.563	17.239	17.943

Player C demonstrated optimal performance at a hop take-off velocity of **9.35 m/s** and an angle of **17°**, reaching a simulated total jump distance of **17.94 m**—an elite-level result that places the athlete within international standards.

CONCLUSION

This study provides a data-driven framework for understanding how anthropometric and biomechanical characteristics influence triple jump performance in under-17 male athletes. Through the application of statistical and machine learning models, we established that variables such as leg length, arm span, and height are significant predictors of triple jump distance. Among the models used, Support Vector Regression (SVR) demonstrated the highest predictive accuracy, validating its effectiveness for forecasting jump performance in youth athletes. The strong correlation between specific body dimensions and performance outcomes reinforces the importance of integrating anthropometric profiling into early-stage athlete development programs. Several studies have explored the relationship between anthropometric characteristics and performance in jump-based events. Carter and Heath's foundational work on somatotyping highlighted the importance of body composition and physical proportions in athletic specialization [11]. Mesomorphic athletes with well-developed musculature were shown to perform better in power-intensive events like the triple jump. Hay's biomechanical analysis of the triple jump emphasized the influence of body segment alignment and ground contact dynamics on jump performance. His findings confirmed that technical efficiency is strongly modulated by the athlete's anthropometric features, particularly leg segment length and take-off angles [12]. Luhtanen and Komi further studied triple jump dynamics by examining mechanical power output in relation to limb proportions. They found that longer lower limbs contribute to improved propulsion during the hop and step phases, supporting the biomechanical advantage theory [13]. Ackland et al. discussed the use of anthropometric data in sport selection and performance evaluation. Their research on youth athletes showed that early physical profiling can be used to guide training interventions and identify future talent in power- and skill-based events [14]. Pion et al. demonstrated the integration of anthropometry with physical performance metrics to predict outcomes in youth sports. Their model used leg length, height, and limb girth as primary features for evaluating jumping potential and injury risk [15]. Malina and Bouchard stressed the role of biological maturity in interpreting anthropometric data in adolescents. They noted that performance variance in U-17 athletes is often linked to maturity status, necessitating age-adjusted predictive modelling for fair comparisons [16]. Cabarkapa et al. employed regression and machine learning algorithms to analyze the predictive power of body composition metrics in sprint and jump events. Their model achieved high accuracy and demonstrated that even simple anthropometric variables can effectively forecast athletic performance [17]. Coh et al. investigated the biomechanics of triple jumpers and noted that physical asymmetry and segmental coordination significantly affect jump execution. Their work also emphasized the need for technical correction based on individual body mechanics [18]. Miller et al. analysed the effects of tibia length and hip width on jump take-off velocity using motion analysis and force platforms. They concluded that these features could serve as strong predictors of horizontal distance covered during the triple jump [19]. Lloyd and Oliver promoted the use of integrated profiling systems combining anthropometric, biomechanical, and neuromuscular assessments. Their approach has become a benchmark for youth athletic screening and has proven effective in minimizing injury while maximizing potential [20]. Anthropometric characteristics significantly impact triple jump performance by affecting biomechanical efficiency, force production, segmental coordination, and take-off mechanics. Factors such as height, body composition, leg length, limb proportions, and muscular development are important, but should be assessed alongside technical skills, neuromuscular capacity, and biological maturity. A comprehensive approach that combines anthropometric profiling, biomechanical analysis, and performance assessment is recommended for athlete evaluation and training development. For U-17 athletes, considerations of growth and maturation are crucial for fair assessments and appropriate training. Future research should focus on these relationships using larger samples and longitudinal studies to clarify the roles of anthropometric variables in performance. Ultimately, anthropometric assessments should support, not replace, direct performance testing and technical evaluations in the training of young triple jumpers.

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AUTHOR CONTRIBUTIONS

Prakash. Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Visualization, Writing – original draft, Writing – review and editing. **Sigamani Jayasingh Albert**

Chandrasekar. Conceptualization, Project administration, Resources, Supervision, Validation, Formal analysis, Funding acquisition, Writing – review and editing. **Sivarani Sivakozhundhu:** Conceptualization, Methodology, Project administration, Resources, Formal analysis, Funding acquisition. **Thamaraiselvi Saravanakumar.** Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Project administration, Software, Validation, Visualization, Writing – original draft, Writing – review and editing.

CONFLICT OF INTEREST. The authors have no conflicts of interest in the material presented in this article.

AI POLICY. The authors declare that no generative AI was used in this manuscript.

DATA AVAILABILITY. The datasets utilized and analysed in this study can be obtained from the corresponding author upon reasonable request. All data necessary to assess the conclusions drawn in this paper are included within the paper itself.

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