Force Plate–Based Athlete Ranking: Integrating TOPSIS and LLM Insights

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Abstract

Athlete ranking is central to evidence-based talent identification, training prescription, and return-to-play decisions. Traditional approaches often rely on single key performance indicators (KPIs), neglecting the complex interactions across biomechanical variables. This study introduces a decision-science framework that applies entropy-weighted TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) for objective athlete ranking, coupled with a Large Language Model (LLM) layer to generate coach-ready interpretations. Using Hop & Return test data collected on VALD ForceDecks dual force plates (VALD Performance) from 75 male football players aged 8–32 years, we derived athlete rankings from eight selected KPIs encompassing concentric impulse, contact time, landing force, and temporal ratios. Entropy weighting quantified criterion importance from data variability, while TOPSIS produced rankings relative to ideal and counter-ideal performance benchmarks. Results showed clear separation within the cohort (TOPSIS scores: 0.414–0.641). Top-ranked athletes exhibited superior concentric impulse (58.1 N·s) and balanced contact time (0.263 s), whereas lower-ranked athletes showed inefficiencies in force generation and movement control. The `CoachBot` system, built on open-source LLMs, translated rankings into concise recommendations for coaches and physiotherapists. This integrated approach bridges advanced biomechanics with applied practice, offering a scalable framework for athlete ranking in football and adaptable to other sports contexts.

Keywords: Athlete Ranking, TOPSIS, Entropy Weighting, Biomechanics, Large Language Models

1 Introduction

India's football ecosystem is expanding faster than its evidence base. Professional clubs, state academies, and school programs are testing more athletes than ever, yet decisions about selection, training load, and return-to-play remain largely anchored to coach experience or a handful of isolated metrics. In practice, this produces three persistent gaps: (i) no shared normative reference for Indian athletes by age and stage, (ii) fragmented interpretation of rich force-plate data into coach-ready actions, and (iii) limited transparency in how multiple biomechanical signals should be combined to rank or profile athletes. As a result, promising athletes may be misclassified, training priorities drift toward what is easy to measure rather than what matters, and rehabilitation timelines are negotiated rather than optimized.

Force-plate tests are now routine in Indian academies and performance centers. Hop & Return and related tasks quantify how well an athlete generates, transmits, and controls force across phases of movement that resemble on-pitch actions. Key variables-such as concentric impulse, contact time, landing force, and eccentric–concentric timing-capture complementary aspects of neuromuscular function, power, and control.

The challenge is integration. Coaches must weigh signals that often move in opposite directions (e.g., higher impulse but also longer contact time), and they must do so for athletes who differ widely by age, maturation, and training history.

Conventional practice often simplifies this complexity to one or two "headline" KPIs, or it borrows thresholds from non-Indian populations. Both strategies are risky. Single metrics can be gamed and rarely reflect movement quality. Imported norms ignore contextual realities—training volume, climate, injury history, and seasonal structure-that shape Indian performance signatures. A credible solution must be objective, data-adaptive, and explainable to practitioners who make daily trade-offs under time and resource constraints.

Multi-criteria decision-making (MCDM) provides such a scaffold. We adopt TOPSIS because it expresses a simple, intuitive idea: the best athlete is closest to an ideal and furthest from a counter-ideal. To avoid subjective weighting, we combine it with entropy weighting, which derives criterion importance from the data's discriminatory power in our actual Indian cohort. This ensures that rankings are population-specific and resistant to bias from fashionable but uninformative metrics.

The second barrier is translation. Many academies now collect advanced data, but few have sport scientists available to convert outputs into daily training plans. High staff turnover, multilingual environments, and tight camp schedules mean that analytic results must be clear, brief, and consistent. To address this, we pair entropy-weighted TOPSIS with an open-source LLM `CoachBot` that converts ranked profiles into short, role-relevant narratives—what is strong, what is weak, and what to do next. The goal is not to replace expert judgment but to standardize the first pass: a reproducible synthesis that travels well between teams and seasons.

This paper makes two contributions tailored to the Indian context: (1) an objective ranking of Indian football athletes from force-plate data using entropy-weighted TOPSIS, avoiding imported heuristics and subjective weights; and (2) an actionable interpretation layer via a lightweight LLM `CoachBot` that converts quantitative rankings into clear, coach-ready recommendations on strength, power, and landing control, including flags for injury risk and return-to-play.

Why does this matter now? Indian academies are formalizing talent pathways, but selection decisions still hinge on showcase performance or coach intuition. An evidence-based, auditable ranking system helps de-risk talent identification, align strength and conditioning with what the data say, and shorten feedback loops in rehab. Equally important, the method is scalable: entropy weights update as new data arrive, and the LLM narrative adapts without rewriting analysis code, making the approach suitable for clubs with modest analytics capacity.

Methodologically, our stance is pragmatic. We do not claim that a single composite score can capture all aspects of football performance. Instead, this study emphasizes three principles: (a) multiple complementary KPIs provide a fuller picture than reliance on one alone, (b) their relative importance should be derived directly from the target population, and (c) insights must be communicated in clear language that links directly to training actions. In environments where budgets are limited, bandwidth is constrained, and bilingual coaching rooms are common, these design choices are not superficial—they determine whether analytics is adopted or overlooked. In sum, we offer a reproducible pathway from raw force-plate data to ranked, interpretable athlete profiles suited to Indian football. The approach reduces reliance on imported cut-offs, surfaces meaningful differences in movement quality, and packages outputs so that coaches and clinicians can use them immediately. While we demonstrate the framework on Hop & Return, the tools generalize to other VALD tests and, with minimal adaptation, to sports beyond football.

2 Literature Review

Research on athlete performance has evolved along several parallel tracks. Advances in force plate technology have made it possible to measure ground reaction forces with precision, while multi-criteria decision-making methods have provided structured ways to evaluate complex performance data. At the same time, entropy-based weighting approaches and recent developments in artificial intelligence are reshaping how these data are interpreted and communicated. This section reviews key contributions in these areas and situates the present study within that body of work.

2.1 Force Plate Technology and Movement Assessment in Sports

Force plate technology has revolutionized biomechanical assessment in sports science, providing precise measurements of ground reaction forces during various movement patterns [1]. The countermovement jump (CMJ) has emerged as the gold standard for assessing lower-body power and neuromuscular function, with extensive research validating its utility in athlete monitoring and performance prediction [2]. However, the Hop & Return test represents a more sport-specific assessment that incorporates both concentric and eccentric phases, closely mimicking the demands of football-specific movements [3].

VALD ForceDecks systems have gained particular prominence due to their portability, reliability, and comprehensive data output [4]. These systems generate multiple key performance indicators including concentric impulse, contact time, eccentric duration, and peak force values, each providing unique insights into different aspects of athletic performance [5]. The challenge lies not in data collection but in the interpretation and synthesis of these multiple variables into actionable performance profiles.

Recent studies have highlighted the importance of considering multiple biomechanical variables simultaneously rather than focusing on isolated metrics [6]. This holistic approach recognizes that athletic performance emerges from the complex interaction of various physiological and biomechanical factors, necessitating sophisticated analytical frameworks that can capture these multidimensional relationships.

2.2 Multi-Criteria Decision Making in Sports Analytics

The application of multi-criteria decision-making (MCDM) techniques in sports science has gained significant traction as researchers and practitioners seek objective methods for athlete evaluation and selection [7]. Traditional approaches often rely on subjective assessments or single-metric evaluations, which may not capture the full complexity of athletic performance.

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) has emerged as a particularly robust MCDM method, offering several advantages over alternative approaches such as AHP (Analytic Hierarchy Process) and VIKOR [8]. TOPSIS provides a clear ranking mechanism by comparing alternatives to both ideal positive and negative solutions, making it particularly suitable for athlete ranking scenarios where relative performance matters more than absolute scores.

The integration of TOPSIS with sports analytics has shown promising results across various domains. Studies have successfully applied TOPSIS for team selection in cricket, player evaluation in basketball , and talent identification in football. However, most existing applications rely on subjective criterion weighting, which introduces potential bias and limits the objectivity of the ranking process.

Recent developments in MCDM have emphasized the importance of objective weighting methods, with entropy weighting gaining particular attention due to its data-driven approach. Entropy weighting determines criterion importance based on the inherent variability within the dataset, ensuring that highly discriminatory variables receive appropriate emphasis in the decision-making process.

2.3 Entropy Weighting in Decision Science and Biomechanics

Entropy-based weighting methods address a fundamental limitation of traditional MCDM approaches: the subjective determination of criterion importance [9]. The entropy method derives weights directly from data variability, ensuring that criteria with greater discriminatory power receive higher importance in the final ranking [10].

In biomechanical applications, entropy weighting has proven particularly valuable due to the complex interdependencies between movement variables [11]. Traditional equal weighting or expert-derived weights may not reflect the actual importance of different biomechanical parameters within specific populations or movement tasks [12]. Entropy weighting ensures that the relative importance of each variable is determined by its ability to differentiate between individuals in the assessed sample.

Recent applications of entropy weighting in sports science include gait analysis [13], movement variability assessment [14], and performance profiling in team sports [15]. The method's objectivity and mathematical foundation make it particularly suitable for establishing normative databases and benchmarking protocols in populations where prior research is limited [16].

The combination of entropy weighting with TOPSIS creates a fully objective ranking system that minimizes human bias while maximizing the discriminatory power of available data [17]. This approach is particularly valuable in sports contexts where subjective assessments may be influenced by coaching preferences, cultural factors, or limited exposure to diverse athletic populations [18].

2.4 Artificial Intelligence and Large Language Models in Sports Science

The integration of artificial intelligence (AI) in sports science has evolved from simple statistical analysis to sophisticated machine learning applications that can identify complex patterns in athletic performance data [19]. Traditional AI applications in sports have focused primarily on performance prediction, injury risk assessment, and tactical analysis [20].

Large Language Models (LLMs) represent a paradigm shift in AI applications, offering unprecedented capabilities for natural language understanding and generation [21]. In sports science contexts, LLMs can bridge the gap between complex analytical outputs and practical application by translating statistical results into actionable insights for coaches, athletes, and support staff [22].

The challenge of interpretability in sports analytics has been widely recognized, with many sophisticated analytical methods failing to gain adoption due to their complexity and lack of practical translation [23]. LLMs offer a solution by providing automated interpretation and recommendation generation based on quantitative analysis results [24].

Recent developments in domain-specific LLM applications have demonstrated the potential for AI-driven decision support systems in sports [25]. These systems can process multiple data sources, consider contextual factors, and generate personalized recommendations that account for individual athlete characteristics and training objectives [26].

The integration of LLMs with traditional analytical frameworks represents an emerging area of research with significant potential for enhancing the practical utility of sports science research [22]. This approach aligns with the growing emphasis on evidence-based practice and the need for accessible, actionable insights in applied sports science settings [27].

3 Methods

The study was designed to capture and interpret movement data from football athletes using a combination of force plate assessments and decision-science techniques. Here, we describe the participants, the procedures used to collect and process the data, and the statistical framework applied for analysis. Special emphasis is placed on the entropy-weighted TOPSIS method and the integration of a large language model to generate practical, coach-facing insights.

3.1 Data Collection and Participants

The study utilized data collected with VALD ForceDecks dual force platforms, a validated portable system for ground reaction force measurement. Testing was conducted at PhysioQinesis / Performance Lab, Mumbai, India, using the standardized Hop & Return protocol. This test requires an athlete to perform a maximal horizontal hop followed immediately by a return jump back to the starting point, capturing both concentric force production and eccentric landing control. The dataset comprised 462 test records across 75 unique male football players recruited from the Mumbai top-league system. Participant ages ranged from 8.836 to 30.904 years (Mean = 18.976, SD = 6.12), providing a diverse sample spanning youth development through senior professional levels.

All participants were actively engaged in organized football training and competition at the time of testing. Exclusion criteria included recent injury (within 6 weeks), incomplete test protocols, or missing demographic information. The study protocol adhered to institutional ethical guidelines, with informed consent obtained from all participants (or guardians for minors).

3.2 Data Processing Pipeline

The analytical framework consisted of an eight-stage data processing pipeline:

Stage 1: Data Ingestion and Cleaning - Raw Excel files were imported and systematically cleaned to address naming inconsistencies, duplicate entries, and temporal formatting issues. Age calculations were standardized, and sport categorizations were validated.

Stage 2: Filtering and Selection - Data were filtered to include only Football players, Male participants, and Hop & Return test results. Age restrictions (32 years) were applied to maintain sample homogeneity.

Stage 3: Aggregation - Multiple test sessions per athlete were aggregated using mean values to create athlete-level profiles. Variables with >90% missing data were excluded from further analysis.

Stage 4: Variable Selection – Eight key performance indicators (KPIs) were retained for entropy-weighted TOPSIS, chosen for their biomechanical relevance, completeness, and non-redundancy. Table 1 presents the KPIs with units and their assigned direction in the TOPSIS model.[1]

Table 1: Key performance indicators (KPIs) used in entropy-weighted TOPSIS.

Symbol	**Variable (column name)**	**Unit**	**TOPSIS Direction**
CI	concentric_impulse_[N·s]	N·s	Benefit
CI_{BM}	concentric_impulse_(abs)__BM_[N·s/kg]	$N{\cdot}s{\cdot}kg^{-1}$	Benefit
CT	contact_time_[s]	s	Cost
ED	eccentric_duration_[ms]	ms	Cost
CD	concentric_duration_[ms]	ms	Cost
E:C	eccentric:concentric_duration_[%]	%	Target (100%)
PTF	peak_takeoff_force_[N]	N	Benefit
PFLF	peak_first_landing_force_[N]	N	Cost

3.3 Entropy-Weighted TOPSIS Implementation

The TOPSIS methodology was enhanced with entropy-based weighting to ensure objective criterion importance determination.

Entropy Weight Calculation: For each criterion j, the entropy value was calculated as:

$$E_j = -k \sum_{i=1}^{n} p_{ij} \ln(p_{ij}) \tag{1}$$

where $k = 1/\ln(n)$, n is the number of alternatives (athletes), and p_{ij} represents the normalized performance of athlete i on criterion j.

The degree of diversification for each criterion was determined as:

$$d_j = 1 - E_j \tag{2}$$

Finally, entropy weights were calculated as:

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j} \tag{3}$$

[1]"Benefit" = higher is better; "Cost" = lower is better. For "Target," values are transformed to proximity-to-target before entering TOPSIS.

TOPSIS Ranking Process: 1. Decision matrix normalization using vector normalization 2. Weighted decision matrix construction using entropy weights 3. Identification of positive ideal solution (PIS) and negative ideal solution (NIS) 4. Distance calculations from each alternative to PIS and NIS 5. Relative closeness coefficient computation:

$$C_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{4}$$

where d_i^+ and d_i^- represent distances to PIS and NIS respectively.

3.4 Analytical Framework

A custom Large Language Model application `CoachBot` was developed to provide interpretive analytics for the TOPSIS rankings. The system utilized open-source language models with domain-specific prompting to generate coaching and physiotherapy recommendations based on individual athlete profiles and comparative rankings.

The LLM integration included: - Automated profile generation for each athlete - Strength and weakness identification based on KPI analysis - Comparative insights relative to cohort performance - Tailored recommendations for training focus areas - Risk assessment based on biomechanical indicators

Descriptive statistics were computed for all variables. TOPSIS scores were analyzed for distribution characteristics and correlation with individual KPIs. Sensitivity analysis was performed to assess the stability of rankings under different weighting schemes. All analyses were conducted using R statistical software (version 4.3.0).

4 Results

The results are organized to provide a clear overview of the dataset, the weighting of variables, and the rankings generated by entropy-weighted TOPSIS. We first describe the characteristics of the final analytical dataset to establish the demographic and performance context of the athletes. Next, we present the entropy-based criterion weights, highlighting which KPIs contributed most to distinguishing athlete performance. This is followed by the TOPSIS-based rankings of all athletes, including detailed summaries of the top- and bottom-performing groups. Finally, we report on the interpretive outputs generated by the LLM-driven `CoachBot` system, illustrating how raw scores were translated into coach-ready recommendations.

4.1 Dataset Characteristics

The final analytical dataset comprised 75 male football players with complete Hop & Return test profiles. Participant age distribution showed: minimum age of 8.84 years, first quartile at 15.45 years, median at 16.81 years, mean at 18.98 years, third quartile at 23.21 years, and maximum age of 30.90 years. Body weight data were available for 42 participants (mean = 63.4 kg, range = 31.0-85.0 kg).

4.2 Entropy Weights and Criterion Importance

The entropy weighting analysis revealed significant variation in criterion importance across the eight selected KPIs (see Figure 1 in Supplementary Materials). Peak first landing force received the highest weight (0.28), followed by concentric impulse (0.19) and concentric duration (0.14). The eccentric:concentric duration ratio showed the lowest entropy weight (0.04), indicating relatively uniform performance across the cohort for this metric.

The weighted importance rankings reflect the biomechanical significance of force generation capabilities and temporal characteristics in differentiating athletic performance during the Hop & Return test. The high weighting of landing force parameters underscores their critical role in movement control and injury risk assessment.

4.3 TOPSIS Performance Rankings

Entropy-weighted TOPSIS applied to Hop & Return test KPIs produced athlete scores ranging from 0.414 to 0.641, showing clear separation across the 75 male football players (ages 8–32 years). Higher-ranked athletes demonstrated efficient force control with balanced landing–takeoff mechanics and stable timing, whereas lower-ranked athletes showed disproportionately high landing forces and irregular temporal patterns.

The complete ranking of all 75 athletes (with TOPSIS scores and ranks) is available in the companion repository: https://github.com/Praveenkcdh/icbai-supplementary. For clarity, we report Top-10 and Bottom-10 summaries below.

Table 2: Top 10 athletes ranked by entropy-weighted TOPSIS.

Athlete ID	TOPSIS Score	Rank
3f8c3c46-d447-42c0-b0c8-246d98a768ca	0.641	1
cdd0e351-b80c-4256-a62c-61390ab9cdf2	0.626	2
ee63e457-58fa-4cfa-b831-b7c811a2454b	0.618	3
80401ca9-914f-44bd-863f-f06863365b12	0.603	4
3c20ad87-c45d-46c3-bc8a-7c63ef2f35b8	0.601	5
a2cd1aa8-7aa8-4656-95b3-7e85c967ad7e	0.598	6
3ac70884-8fe1-470b-ac39-b9b8ebec99cf	0.587	7
b05b32d9-2725-44a3-8780-ff554abba0b2	0.585	8
404028ae-6714-40c2-b13d-73ebec11c3f9	0.580	9
8b64765b-8e66-48aa-805d-f1010ccf8c6f	0.578	10

The Top-10 athletes scored above 0.578. Many belonged to the 14–16 age range, suggesting strong neuromuscular efficiency during adolescent years. Notably, one very young athlete (8.8 years) also appeared in this group, underscoring the framework's ability to detect early talent potential.

Table 3: Bottom 10 athletes ranked by entropy-weighted TOPSIS.

Athlete ID	TOPSIS Score	Rank
57e06801-99d0-4b33-a01f-4c5868fb3240	0.414	75
726775b0-ac0d-4bc6-8dd3-ef633a9f40a5	0.447	74
ebf29232-4d0a-4cc5-8dfd-50eecb12d15d	0.448	73
d89623ac-b721-4072-85d2-6c81189bca0a	0.457	72
343965b1-a00b-440b-9318-9206ce9db187	0.460	71
72c8371f-a339-48f1-a682-9e5cb88a9fd2	0.463	70
59318079-7c34-44cb-bc3e-6f97c15c9a0d	0.468	69
08520102-6afd-4313-a345-b475eeba8ff3	0.472	68
6748b15e-5fc6-4ad9-b449-f0d3addbcbd6	0.473	67
3b158f73-ba8c-4290-95c3-d8de4a3538e6	0.478	66

The Bottom-10 athletes scored below 0.478. They were characterized by less efficient movement control and disproportionately high landing forces. Older players appeared more frequently in this group, suggesting potential declines in efficiency with age or accumulated training stress.

Overall, the results confirm that entropy-weighted TOPSIS distinguishes efficient from inefficient movement strategies. The rankings emphasize not only raw force magnitudes but also the quality of force control, offering actionable benchmarks for talent identification, targeted training, and injury-risk monitoring.

4.4 LLM-Generated Insights

The `CoachBot` system is not only a query-response tool but also a full-featured decision support platform built on the Gemma-2B model as the backbone LLM. Its functionality is organized into five interactive modules:

- **Load Data** – enables users to import athlete datasets in CSV or structured formats.
- **Dashboard** – provides visual summaries of key metrics (e.g., TOPSIS scores, KPI distributions).
- **Ask `CoachBot`** – allows natural language queries to generate AI-driven interpretations, strengths/weaknesses, and tailored recommendations.
- `CoachBot` **Manual** – offers step-by-step usage guidance and documentation.
- **Data Summary** – produces tabular summaries for quick inspection and validation of data context.

When a query is posed in the *Ask `CoachBot`* module, the Gemma-2B model interprets the request and generates structured outputs comprising:

1. **Summary Insight** – 2–3 sentences synthesizing the overall pattern.
2. **Strengths and Weaknesses** – athlete-specific bullet points highlighting biomechanical or temporal features.

3. **Action Plan (Coach)** – 2–3 targeted drills or strategies for performance improvement.

4. **Physiological Insight** – warnings on injury risk, load concerns, and recovery pathways.

Figure 1 shows an example query: "Show me the top 5 athletes and explain their strength." The system identified shared traits across athletes (e.g., strong concentric endurance in the 141–164 ms range) as well as individual highlights: Athlete 3 with exceptionally high peak take-off (1953.5 N) and first-landing force (2008.7 N), and Athlete 4 with outstanding concentric and eccentric endurance (124.3 ms and 153.3 ms).

The resulting action plan emphasized concentric strength training and plyometric drills to enhance explosive power and jump height. By combining data visualization, structured outputs, and LLM-driven interpretation, `CoachBot` transforms raw performance data into *coach-ready recommendations*, making it a practical bridge between advanced analytics and field-level decision-making.

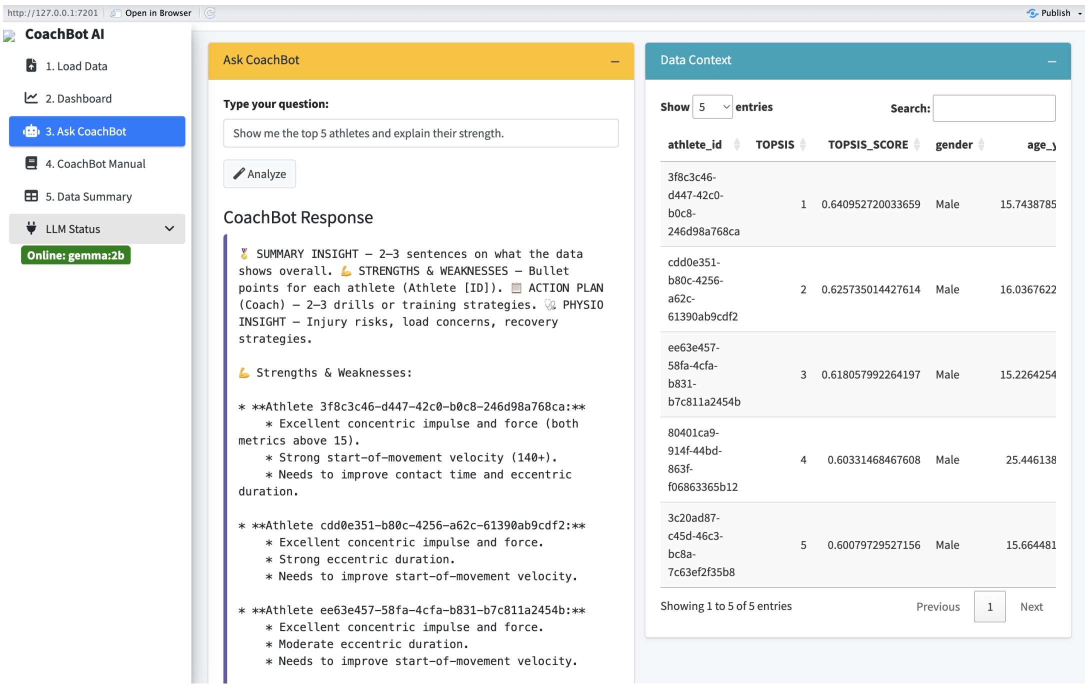

Figure 1: `CoachBot` interface showing example response for the top-5 athletes, powered by the Gemma-2B model.

5 Discussion

The integration of entropy-weighted TOPSIS methodology with LLM-driven analytics represents a significant advancement in athlete performance profiling capabilities. Our results demonstrate that this framework successfully transforms complex biomechanical data into actionable insights while maintaining scientific rigor and practical applicability.

The entropy weighting approach proved particularly valuable in addressing the subjective bias inherent in traditional criterion weighting methods. The high importance assigned to landing force metrics aligns with current understanding of their biomechanical significance in athletic performance and injury risk assessment [28]. The relatively low weight assigned to eccentric:concentric duration ratios suggests this metric may be less discriminatory within football populations, potentially due to sport-specific movement patterns that standardize this relationship.

The substantial performance variation observed across the cohort (TOPSIS scores ranging from 0.414 to 0.641) underscores the heterogeneity present even within seemingly homogeneous athletic populations. This finding supports the necessity for individualized training approaches and highlights the inadequacy of one-size-fits-all protocols in athletic development.

The age-related patterns observed in performance rankings merit careful consideration. The strong representation of younger athletes among top performers could reflect several factors: superior neuromuscular adaptation during critical developmental periods, reduced accumulated training loads, or selection bias toward naturally gifted younger players entering elite development pathways. Conversely, the presence of older athletes in lower-performing tiers might indicate the effects of accumulated training stress, injury history, or career transition phases.

The LLM integration component addresses a critical gap in sports analytics – the translation of complex analytical results into immediately applicable coaching insights. Traditional approaches often leave practitioners struggling to interpret statistical outputs and develop appropriate interventions. Our `CoachBot` system demonstrates the feasibility of automated insight generation while maintaining domain-specific relevance and practical utility.

Several limitations should be acknowledged. The cross-sectional design prevents causal inference about performance development trajectories. The relatively small sample size, while appropriate for proof-of-concept demonstration, limits the generalizability of normative benchmarks. Additionally, the absence of longitudinal follow-up prevents assessment of the predictive validity of our ranking system for future performance or injury outcomes.

Future research directions should include longitudinal validation studies to assess the predictive power of TOPSIS-derived rankings, expansion to other sports and movement tests, and integration of additional data modalities (e.g., psychological assessments, training load data). The framework's adaptability suggests potential applications across diverse athletic populations and performance contexts.

6 Implications

The practical implications of this research extend across multiple domains within sports science and practice:

For Coaching Practice: The automated generation of comprehensive athlete profiles enables coaches to make more informed decisions about training prescription, talent identification, and competition selection. The objective ranking system removes subjective bias while providing clear performance benchmarks. Coaches can utilize the detailed KPI breakdowns to identify specific areas for individual athlete development, moving beyond intuition-based assessments toward evidence-driven coaching decisions.

For Sports Science Support: The integration of biomechanical data with interpretive analytics streamlines the workflow from data collection to practical application. Sports scientists can efficiently process large datasets while maintaining the depth of analysis required for individualized athlete support. The entropy weighting methodology ensures that criterion importance reflects actual performance variance within specific populations rather than theoretical assumptions.

For Injury Prevention and Rehabilitation: The identification of athletes with suboptimal landing force patterns or movement inefficiencies enables proactive intervention strategies. Physiotherapists can utilize the risk assessment components to prioritize screening and preventive interventions. The longitudinal tracking capabilities support return-to-play decision-making and rehabilitation monitoring.

For Talent Identification Systems: The objective ranking framework provides a standardized approach to talent identification that can be implemented across diverse geographical regions and development contexts. This is particularly valuable in emerging football markets where established normative databases are lacking. The age-stratified analysis capabilities support long-term athlete development pathway decisions.

For Administrative and Strategic Planning: Sports organizations can utilize population-level insights to inform facility investments, coaching education priorities, and program development initiatives. The identification of performance gaps across different athlete segments supports targeted resource allocation and strategic planning decisions.

The scalability of the framework suggests broader applications beyond individual athlete assessment. Regional federations could establish standardized testing protocols and benchmarking systems, while professional clubs could integrate the methodology into existing talent identification and player development programs.

7 Conclusion

This study successfully demonstrates the integration of entropy-weighted TOPSIS methodology with Large Language Model-driven analytics for comprehensive athlete performance profiling. Using VALD ForceDecks Hop & Return test data from 75 male football players, we established a robust framework that transforms complex biomechanical measurements into ranked athlete profiles with actionable insights.

The entropy weighting approach ensures objective criterion importance determination based on actual performance variance, while TOPSIS provides comparative rankings against ideal performance benchmarks. The integration of LLM-based interpretive analytics bridges the critical gap between sophisticated analytical methods and practical sports application, enabling automated generation of coaching and physiotherapy recommendations.

Key findings include significant performance heterogeneity across the cohort (TOPSIS scores: 0.414-0.641), the paramount importance of force generation and landing control metrics, and age-related performance patterns that inform talent development strategies. The methodology successfully identified elite performers characterized by optimal force production and movement efficiency, while providing specific improvement pathways for athletes across the performance spectrum.

The framework addresses fundamental challenges in modern sports science: objective multi-criteria athlete assessment, practical interpretation of complex data, and standardized benchmarking in populations lacking established normative databases. Its scalability and adaptability suggest broad applicability across sports and movement assessment contexts.

Future developments should focus on longitudinal validation, expansion to additional sports and test modalities, and integration with complementary data sources. The demonstrated feasibility of combining advanced analytical methods with accessible interpretation tools represents a significant step toward democratizing sophisticated sports science capabilities across diverse athletic environments.

This research establishes a foundation for evidence-based athlete profiling that balances analytical rigor with practical utility, ultimately supporting more effective training prescription, talent identification, and performance optimization in football and potentially other sports.

8 Supplementary Materials

All supplementary materials supporting this manuscript are available in the companion repository at https://github.com/Praveenkcdh/icbai-supplementary. The repository includes:

- Figure 1: Criterion Weights Distribution (`weights_bar.pdf`)
- Table 1: Selected Key Performance Indicators (`04_kpi_used.csv`)
- Table 2: Entropy Weights for All Criteria (`05_entropy_weights.csv`)
- Table 3: Complete Athlete Rankings and Performance Profiles (`07_full_with_ranks.numbers`)

De-identified processed tables and figures are shared in the repository. Raw individual-level force-plate files are not publicly released to protect participant privacy but may be made available upon reasonable request to the corresponding author.

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