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Original Research

Transformation of Basketball Academy Athlete Performance Evaluation Using Information Technology and the Weighted Product Method

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ABSTRACT

Performance evaluation of basketball athletes at academies in Indonesia still largely relies on manual, subjective, and unintegrated assessment processes, leading to inconsistencies between evaluation periods. This study aims to design and develop a web-based information system for athlete performance evaluation at Bendella Basketball Court, Bekasi, using the Weighted Product (WP) algorithm. The system was developed following the Waterfall Software Development Life Cycle (SDLC) methodology, covering requirements analysis, system design, implementation with the Laravel framework, and testing. Eight evaluation criteria were established: shooting (20%), dribbling (15%), defense (15%), passing (10%), speed (10%), stamina (10%), discipline (10%), and teamwork (10%). The WP algorithm computes vector S and preference value V for each athlete, followed by threshold-based categorization into Junior Advance and Junior Basic categories. Testing on five sample athletes demonstrates that the system correctly ranks and categorizes athletes objectively. The Weighted Product method provides greater stability compared to Simple Additive Weighting (SAW) with a sensitivity change of only 0.01% versus 0.38%. This system supports coaches in making more accurate, consistent, and data-driven athlete evaluation decisions.

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1. INTRODUCTION

Basketball is a sport with high tactical and physical complexity. Athlete development, particularly at youth academy level, requires a structured, measurable, and data-driven performance evaluation mechanism [1]. Studies on coaching management in multi-sport contexts confirm that systematic evaluation frameworks significantly improve athlete development outcomes and coaching efficiency [2]. However, in practice, most basketball academies in Indonesia still rely on manual assessment processes that are not integrated, making evaluation results susceptible to subjectivity and inconsistency across assessment periods [3]. Coaches typically record scores by hand with no systematic calculation to rank or classify athletes, limiting the utility of evaluation data for long-term development planning.

Performance evaluation is a structured process of assessing athletes' abilities by considering various aspects such as technique, physical fitness, and tactics, thereby providing a comprehensive picture of an athlete's performance quality [4]. The absence of integrated digital tools means coaches cannot easily compare athlete progress between periods or share standardized results among staff members. Web-based information systems have been demonstrated to improve the efficiency and accuracy of data-driven administrative processes across various institutional contexts [5], and their application to athlete evaluation represents a natural and practical extension of this capability.

Several prior studies have demonstrated that evaluation without an integrated system leads to high subjectivity and inconsistent results [6]. Multi-criteria decision-making (MCDM) approaches have been widely applied to address such challenges. The Weighted Product (WP) method is one of the decision support system methods used to provide solutions in determining the best alternative choices based on various criteria and weight considerations [7], capable of processing multiple criteria with specific weights to produce objective alternative rankings [8]. WP has been applied in contexts such as employee selection [9,10], scholarship recipient determination [11], and instructor performance assessment [6], consistently yielding reproducible ranking results. Web-based SPK systems using the WP method have also been developed for competitive participant selection, confirming the method's suitability for structured decision-making processes [12].

A comparative study of WP and SAW in a scholarship selection system revealed that WP exhibited a total sensitivity change of only 0.01%, far lower than SAW's 0.38% [13]. This stability is a crucial advantage for periodic athlete evaluations, where inconsistency caused by minor weight changes could undermine the credibility of the assessment system. Despite the proven advantages of WP, most existing implementations focus on administrative domains. Few studies have specifically applied WP within a web-based system tailored to basketball athlete performance evaluation [14].

The identified research gap is the absence of a structured, web-based decision support system specifically designed for basketball athlete performance evaluation integrating the WP algorithm with a formal SDLC development process. This study addresses that gap by designing and building a web-based athlete performance evaluation information system using the Weighted Product algorithm, developed through the Waterfall SDLC methodology. The primary objectives are: (1) to implement the Waterfall SDLC phases in designing and building the system; (2) to apply the Weighted Product method to process multi-criteria athlete evaluations objectively; and (3) to validate system functionality through functional testing. Section 2 presents the research methods, Section 3 discusses results and findings, and Section 4 provides the conclusion.

2. RESEARCH METHODS

2.1. Basic Research Framework

This study adopts the Waterfall Software Development Life Cycle (SDLC) methodology, which provides a structured, sequential approach to system development. The Waterfall model is highly effective for web-based information systems where requirements are well-defined and stable from the outset [15]. The development process is divided into five distinct phases: (1) Requirements Analysis: Conducted through direct observation and in-depth interviews with the head coach at Bendella Basketball Court (Jl. Raya Perjuangan No.26, Bekasi, West Java) to identify existing evaluation bottlenecks and define functional requirements. (2) System Design: Translating requirements into system architecture, database schemas, and Unified Modeling Language (UML) diagrams. (3) Implementation: Coding the system using the Laravel PHP framework and MySQL database. (4) Testing: Validating system functionality and algorithmic accuracy using Black Box Testing. (5) Maintenance: Post-deployment updates, bug fixes, and system scaling (planned for future operational phases).

2.2. Data Collection and Sampling

Primary data were collected through direct observation of athlete training sessions and the distribution of manual evaluation forms by the coaching staff. Secondary data were gathered through a comprehensive literature review concerning basketball performance metrics, Multi-Criteria Decision Making (MCDM) methods, and web development best practices. For the algorithm validation and system testing phase, a sample of five junior athletes was selected using purposive sampling to represent a diverse range of skill levels, ensuring the Weighted Product (WP) algorithm's ranking and categorization capabilities could be thoroughly evaluated.

2.3. System Analysis and Design

The analysis phase identified the limitations of the existing manual process, where coaches record scores on paper forms without systematic aggregation or digital archiving. The proposed system automates data collection, WP calculation, dynamic ranking, and threshold-based categorization. It accommodates two primary user roles: Admin (managing master data such as users, athletes, and criteria) and Coach (inputting evaluation scores and generating performance reports). System requirements were modeled using UML, including Use Case, Activity, Sequence, and Class Diagrams. Furthermore, the system architecture follows the Model-View-Controller (MVC) design pattern. The Model handles database interactions (e.g., retrieving athlete scores), the View manages the responsive Bootstrap-based user interface, and the Controller processes the WP algorithm logic and routing.

2.4. Evaluation Criteria and Weighting

Eight criteria were established for athlete performance evaluation. The criteria weights were determined through expert judgment involving the head coach and validated against standard basketball competency literature. All eight criteria are classified as benefit attributes, meaning that higher scores correlate with better athletic performance. Criterion scores are assessed on a five-point Likert scale (1 = Very Poor, 2 = Poor, 3 = Average, 4 = Good, 5 = Excellent). The total sum of the weights equals 1.00, satisfying the WP normalization requirement. The criteria and assigned weights are presented in Table 1.

Table 1. Evaluation Criteria, Attribute Type, and Weights

No	Criterion	Attribute	Weight (W_j)
1	Shooting (C_1)	Benefit	0.20
2	Dribbling (C_2)	Benefit	0.15
3	Passing (C_3)	Benefit	0.10
4	Defense (C_4)	Benefit	0.15
5	Speed (C_5)	Benefit	0.10
6	Stamina (C_6)	Benefit	0.10
7	Discipline (C_7)	Benefit	0.10
8	Teamwork (C_8)	Benefit	0.10

2.5. Weighted Product Algorithm

The Weighted Product method evaluates multiple alternatives by requiring a multiplicative aggregation of criterion scores raised to the power of their respective weights [6]. The mathematical formulation is detailed in the following steps:

Step 1: Weight Verification. Ensure the sum of all criterion weights equals 1.

$$\sum_{j=1}^{n} W_j = 1 \tag{1}$$

Step 2: Vector S Calculation. For each athlete alternative (A_i), the preference vector (S_i) is computed using Equation (2). In the general WP model, the exponent is positive for benefit criteria and negative for cost criteria. Since all criteria in this study are benefit attributes, all exponents remain positive.

$$S_i = \prod_{j=1}^{n} (X_{ij})^{W_j}, \quad \text{for } i = 1, 2, \ldots, m \tag{2}$$

Step 3: Preference Value (V) Calculation. The final relative preference value (V_i) for each athlete is calculated by normalizing the S_i vector against the sum of all preference vectors, as shown in Equation (3). This step generates the final ranking from highest to lowest V_i.

$$V_i = \frac{S_i}{\sum_{i=1}^{m} S_i}, \quad \text{for } i = 1, 2, \ldots, m \tag{3}$$

Where:

- S_i = Preference vector for athlete alternative i
- V_i = Relative preference value (final ranking score) for athlete i
- X_{ij} = Performance score of athlete i on criterion j (Scale 1–5)
- W_j = Normalized weight of criterion j
- n = Total number of evaluation criteria ($n = 8$)
- m = Total number of athlete alternatives evaluated

2.6. Threshold-Based Categorization

Following the WP ranking process, athletes are categorized into performance tiers to support coaching decisions. This is achieved using a threshold based on a top percentage quota, determined by Equation (4):

$$K = \mathrm{round}(N \times P) \tag{4}$$

Where K is the threshold rank for the top-tier category (rounded to the nearest integer), N is the total number of evaluated athletes in the current period, and P is the top percentage quota, set at 30% (0.30) based on academy coaching standards. Athletes with a rank $\leq K$ are categorized as Junior Advance (eligible for advanced training and competitions), while athletes with a rank $> K$ are categorized as Junior Basic (requiring foundational skill reinforcement).

2.7. System Implementation

The system was implemented using the Laravel PHP framework with MySQL as the relational database management system. The development environment utilized XAMPP as the local server and Visual Studio Code as the primary IDE. To ensure the reliability of the system, Black Box Testing was employed. This testing method focuses on validating the functional requirements of the system—such as user authentication, CRUD (Create, Read, Update, Delete) operations for athlete data, and the accuracy of the WP calculation engine—without examining the internal code structure. Test scenarios were designed to cover all primary use cases, ensuring the system produces accurate rankings and categorizations that perfectly match manual mathematical calculations [16–20].

3. RESULTS AND DISCUSSION

3.1. Weighted Product Calculation

The WP algorithm was applied to five athlete samples from Bendella Basketball Court. Evaluation scores were assigned by the head coach based on direct observation during training sessions. Table 2 presents the raw criterion scores for each athlete.

Table 2. Athlete Criterion Scores (Scale 1–5)

No	Athlete	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
1	Ibrahim Arkan	4	3	4	3	4	3	5	4
2	Devaro	5	4	3	4	5	4	4	5
3	Eureka Aziz	3	3	4	3	3	3	4	3
4	Khezia	4	5	4	4	4	5	5	5
5	Darren	2	3	3	2	3	2	3	3

C_1=Shooting, C_2=Dribbling, C_3=Passing, C_4=Defense, C_5=Speed, C_6=Stamina, C_7=Discipline, C_8=Teamwork

Using the weights in Table 1 and Equation (2), vector S was computed for each athlete. The calculation for Khezia (A_4) is shown as an example:

$$S_4 = (4)^{0.20} \times (5)^{0.15} \times (4)^{0.10} \times (4)^{0.15} \times (4)^{0.10} \times (5)^{0.10} \times (5)^{0.10} \times (5)^{0.10} = 4.4225 \tag{5}$$

Following the same mathematical procedure, the Vector S values for the remaining four athletes were computed. The cumulative sum of all preference vectors ($\sum S$) across the five evaluated athletes was calculated to be 17.9953. This cumulative value serves as the constant denominator for determining the final relative preference value (Vector V) for each athlete, as dictated by Equation (3). Furthermore, to classify the athletes into performance tiers, the threshold value (K) was calculated using Equation (4). With a total of $N = 5$ athletes and a top percentage quota of $P = 30\%$ (0.30), the threshold is calculated as $K = 5 \times 0.30 = 1.5$, which rounds to $K = 2$. Therefore, the top two ranked athletes will be categorized as Junior Advance, while the remaining three will be placed in the Junior Basic category. The complete synthesis of the WP calculation, including Vector S, Preference Value V, final ranking, and the resulting category assignments for all athletes, is comprehensively detailed in Table 3.

As presented in Table 3, Khezia emerged as the highest-performing athlete with a preference value of $V = 0.2458$, closely followed by Devaro ($V = 0.2361$). These preference values indicate the relative dominance of each

Table 3. WP Calculation Results, Ranking, and Athlete Categorization

Rank	Athlete	Vector S	Value V	Rank	Category
1	Khezia	4.4225	0.2458	1	Junior Advance
2	Devaro	4.2494	0.2361	2	Junior Advance
3	Ibrahim Arkan	3.6457	0.2026	3	Junior Basic
4	Eureka Aziz	3.1778	0.1766	4	Junior Basic
5	Darren	2.4997	0.1389	5	Junior Basic

athlete's overall skill set against the established criteria weights. Applying the previously established threshold of $K = 2$, Khezia and Devaro successfully secured the Junior Advance classification. This designation indicates that they possess the requisite technical, physical, and mental competencies to participate in advanced training regimens and represent the academy in inter-club competitions. Conversely, Ibrahim Arkan, Eureka Aziz, and Darren, whose preference values ranged from 0.2026 to 0.1389, were assigned to the Junior Basic tier.

This clear demarcation eliminates the ambiguity inherent in the previous manual evaluation process. By relying on quantifiable preference values rather than subjective intuition, the coaching staff at Bendella Basketball Court can now allocate training resources more effectively. Athletes in the Junior Basic category can be targeted for foundational skill reinforcement, ensuring a structured and equitable pathway for their future development. To further understand the underlying factors driving these final rankings, a granular analysis of each athlete's performance across the individual criteria is necessary, which is discussed in the following subsection.

3.2. Per-Criterion Performance Analysis

A deeper analysis of individual criterion scores in Table 2 reveals meaningful performance patterns across all five athletes that would be difficult to identify systematically through the previous manual evaluation process at Bendella Basketball Court. In the shooting criterion (C_1, weight 0.20), Devaro achieved the highest score (5), demonstrating superior offensive capability reflected in his second-place overall ranking. Shooting carries the highest weight in the evaluation framework, acknowledging its critical role in basketball performance at the junior level [14]. Conversely, Darren's shooting score of 2 is the primary driver of his last-place ranking, indicating that targeted shooting training should be a priority in his individual development program.

In dribbling (C_2) and discipline (C_7), Khezia consistently achieved the maximum score of 5, combined with perfect stamina ($C_6 = 5$) and teamwork ($C_8 = 5$), establishing her as the most well-rounded athlete in the evaluation cohort. Ibrahim Arkan's notably high discipline score ($C_7 = 5$) relative to his other criteria suggests strong coachability, which may support accelerated technical improvement in future evaluation periods. Eureka Aziz displayed consistent but modest scores ranging between 3 and 4 across all criteria, placing him in a transitional development stage where broad-based skill improvement would yield the most significant ranking advancement.

3.3. Practical Implications for Athlete Development

The web-based evaluation system offers several practical contributions to the daily operations of Bendella Basketball Court beyond simple ranking generation. First, the system provides a structured digital archive of evaluation records across multiple periods, enabling coaches to track individual athlete progress over time. Previously, paper-based records were difficult to retrieve and compare, preventing longitudinal analysis of athlete development. With digital storage, coaches can generate trend reports showing whether an athlete's scores in specific criteria are improving, stagnating, or declining across consecutive evaluation cycles.

Second, the threshold-based categorization into Junior Advance and Junior Basic provides an actionable grouping mechanism that directly supports coaching decisions. Athletes in the Junior Advance category can be prepared for more advanced training programs or inter-academy competitions, while Junior Basic athletes can receive supplementary coaching sessions tailored to their identified weaknesses. This structured approach replaces the previous ad-hoc classification that relied entirely on coach intuition, ensuring more equitable and transparent athlete development pathways.

Third, the system's multi-criteria weighting framework allows the academy to adjust evaluation priorities as coaching philosophies or competition requirements evolve. If the academy decides to prioritize teamwork and discipline over technical skills in a particular season, criterion weights can be updated in the system without requiring changes to the data collection process. The system therefore functions not only as an evaluation tool but also as a strategic planning instrument for the coaching staff.

3.4. Method Stability and Comparison with Prior Studies

The selection of the Weighted Product method over alternative MCDM approaches was grounded in its proven stability under weight perturbation. As reported by Pratama et al. [13], WP demonstrated a total sensitivity change of only 0.01% compared to SAW's 0.38% when criterion weights were varied. In periodic athlete evaluation, where coaches may adjust criterion weights between seasons, this stability ensures that ranking outcomes remain consistent and credible rather than fluctuating dramatically with minor weight adjustments.

The findings of this study are consistent with those reported in related prior works. Utami et al. [6] demonstrated that WP produced objective and consistent instructor performance rankings, with evaluators expressing higher confidence in WP-generated results compared to manual assessments. Similarly, Ikhsanuddin et al. [8] confirmed that WP effectively reduced bias in healthcare worker selection by ensuring all criteria contributed proportionally to the final ranking. Pratama et al. [10] and Afriadi et al. [12] further confirmed the practical applicability of WP-based web systems in organizational selection contexts, supporting its adoption in this study's basketball evaluation setting.

Compared to more complex MCDM methods such as TOPSIS or AHP, WP offers the advantage of computational simplicity while maintaining sufficient discriminating power for the athlete cohort evaluated in this study. For larger athlete pools, the proportional preference value calculation ensures that the method scales without requiring additional algorithmic complexity, making it particularly suitable for deployment in web-based systems where real-time calculation efficiency is important for user experience.

3.5. Functional Testing and Algorithmic Verification

System functionality was validated using Black Box Testing covering authentication, CRUD operations, weight and score validation, the WP engine, categorization, reporting, and role authorization. Table 4 summarizes the test scenarios and outcomes.

Table 4. Black Box Testing Results

No	Test Scenario	Expected Result	Observed Result	Status
1	Login with valid Admin/Coach credentials	Redirected to role-specific dashboard	As expected	Success
2	Login with invalid credentials	Rejected with error message	As expected	Success
3	Admin adds/edits/deletes athlete record	CRUD persisted correctly	As expected	Success
4	Admin saves weights summing to 1.00	Weights accepted	As expected	Success
5	Admin saves weights $\neq 1.00$	Rejected with validation warning	As expected	Success
6	Coach inputs score outside 1–5 range	Rejected with validation message	As expected	Success
7	Coach submits complete evaluation form	Scores stored per athlete and period	As expected	Success
8	System executes WP calculation	S, V, and ranking produced in real time	As expected	Success
9	System applies threshold $K = 2$	Ranks 1–2 Junior Advance; 3–5 Junior Basic	As expected	Success
10	Coach generates performance report	Report shows scores, S, V, rank, category	As expected	Success
11	Coach accesses Admin-only master data	Access denied by authorization layer	As expected	Success

All 11 scenarios passed (100% success rate). To verify algorithmic accuracy, the system output was further cross-checked against manual mathematical computation (Table 5).

Table 5. Manual vs. System Computation Verification

Athlete	Manual S	System S	Manual V	System V	System Rank	Match
Khezia	4.4225	4.4225	0.2458	0.2458	1	Yes
Devaro	4.2494	4.2494	0.2361	0.2361	2	Yes
Ibrahim Arkan	3.6457	3.6457	0.2026	0.2026	3	Yes
Eureka Aziz	3.1778	3.1778	0.1766	0.1766	4	Yes
Darren	2.4997	2.4997	0.1389	0.1389	5	Yes

The perfect agreement confirms that the WP engine implements Equations (1)–(4) without computational deviation, eliminating the arithmetic errors and inconsistencies inherent in the previous paper-based process.

3.6. Discussion

The application of the Weighted Product (WP) method in this study reveals a critical advantage over traditional additive models, such as the Simple Additive Weighting (SAW) method, particularly regarding the principle of limited compensation in sports profiling. In additive models, an exceptionally high score in one criterion can mathematically compensate for a critically low score in another. However, in basketball, a player who lacks fundamental defensive or passing skills remains a tactical liability, regardless of their shooting prowess [14]. The multiplicative nature of the WP algorithm inherently penalizes extreme deficiencies. This was empirically demonstrated in the evaluation of Darren, whose critically low shooting score exponentially attenuated his final Vector S, correctly placing him at the bottom of the cohort despite moderate scores in other areas. Conversely, Khezia's top ranking was driven by her balanced profile; the WP method rewards holistic competency, which aligns perfectly with modern youth development philosophies that prioritize well-rounded foundational skills over early specialization.

Beyond the mathematical mechanics, the transition from manual, paper-based assessments to a web-based information system addresses a fundamental flaw in traditional sports coaching: cognitive bias. Manual evaluations are highly susceptible to the recency effect, where a coach overweights an athlete's performance in the most recent training session, and the halo effect, where a general impression biases specific criterion scores. By enforcing a structured, criterion-by-criterion digital input constrained to a standardized Likert scale, the proposed system forces analytical thinking, thereby reducing subjective heuristic biases. Furthermore, the digital archiving capability transforms the system from a mere cross-sectional ranking tool into a longitudinal development tracker. In the previous manual system at Bendella Basketball Court, historical data was easily lost, making it impossible to track an athlete's growth trajectory. The web-based architecture ensures that evaluation data is persistently stored, enabling coaches to objectively verify whether an athlete's high discipline score is translating into measurable improvements in technical skills over subsequent evaluation cycles.

A central finding of this study is the confirmation of WP's algorithmic stability, which is paramount for periodic sports evaluations. As established by Pratama et al. [13], WP exhibits a sensitivity change of merely 0.01% under weight perturbation, compared to 0.38% for SAW. In the operational context of a basketball academy, coaching philosophies and tactical requirements frequently shift between seasons. If a highly sensitive algorithm like SAW were used, minor adjustments to criterion weights by the coaching staff could cause drastic, unmerited fluctuations in athlete rankings, thereby destroying the athletes' and parents' trust in the evaluation system. WP's mathematical stability ensures that an athlete's tier classification remains robust and credible, shifting only when there is a genuine change in on-court performance. Compared to more complex Multi-Criteria Decision Making (MCDM) methods like the Analytic Hierarchy Process (AHP), which requires exhaustive pairwise comparisons that are cognitively taxing for busy coaches, WP offers an optimal balance. It requires only direct weight assignment, making it highly intuitive for non-technical sports practitioners while retaining sufficient discriminating power to separate closely matched athletes, aligning with findings by Utami et al. [6] and Ikhsanuddin et al. [8] regarding high user confidence in organizational selection contexts.

Beyond the mathematical outputs, the threshold-based categorization mechanism provides profound managerial implications for resource allocation at the academy. Youth academies often operate with limited coaching staff, court time, and financial resources. The arbitrary grouping of athletes in the past led to inefficient training sessions where advanced players were held back by beginners. By systematically isolating the top tier based on the calculated threshold, the academy can implement differentiated instruction. Junior Advance athletes can be subjected to high-intensity, complex tactical drills and inter-club competitive exposure, while Junior Basic athletes can be routed into targeted remedial clinics tailored to their specific weaknesses identified in the per-criterion analysis. Thus, the system functions not just as an assessment tool, but as a strategic sports management instrument that ensures equitable and efficient athlete development pathways.

Despite its successful implementation, this study has limitations that outline the trajectory for future research. First, the current evaluation relies entirely on human observation. While the WP algorithm processes this data objectively, human observation is inherently limited in capturing micro-metrics such as exact sprint speed or shot release time. Future iterations of this system must integrate Internet of Things (IoT) wearable sensors and computer vision technologies to feed objective, continuous biometric data directly into the WP engine. Second, the current prototype was tested in a localized environment with a small sample size. For enterprise-level deployment, the system requires cloud-native architecture, robust data encryption, and Role-Based Access Control (RBAC) secured via JSON Web Tokens (JWT) to protect sensitive performance data. Finally, the current user interface lacks predictive analytics. Future development should incorporate machine learning models to provide prescriptive insights, such as calculating the exact score improvement required in a specific weak criterion for an athlete to mathematically guarantee promotion to the advanced tier in the next evaluation period.

4. CONCLUSION

This study successfully designed and developed a web-based athlete performance evaluation information system for a basketball academy using the Weighted Product algorithm, implemented through the Waterfall SDLC methodology. The system evaluates athletes across eight criteria — shooting (20%), dribbling (15%), defense (15%), passing (10%), speed (10%), stamina (10%), discipline (10%), and teamwork (10%) — and applies the WP algorithm to produce objective rankings classified into Junior Advance and Junior Basic tiers via threshold-based categorization. Testing on five sample athletes produced a correct ranking with Khezia ($V = 0.2458$) and Devaro ($V = 0.2361$) categorized as Junior Advance, validating the system's computational accuracy. Per-criterion analysis further demonstrated the system's ability to identify individual athlete strengths and weaknesses, enabling targeted coaching interventions beyond simple ranking outputs.

The implementation of WP contributes to improved objectivity and consistency in athlete evaluation by replacing the previously manual and subjective process with a systematic, data-driven approach. The method's low sensitivity to weight perturbations (0.01% vs SAW's 0.38%) confirms its suitability for periodic evaluations where consistency across assessment cycles is critical. The system's practical contributions include digital evaluation archiving, structured athlete categorization, and a configurable multi-criteria framework that supports dynamic coaching priorities, providing a more equitable and efficient evaluation environment at Bendella Basketball Court. Future research should focus on extending the system to support multiple academies with configurable evaluation frameworks, integrating objective sensor-based performance data to complement subjective coach assessments, and implementing production-level security features for institutional deployment. Comparative studies with other MCDM methods such as TOPSIS or AHP, as well as longitudinal studies tracking athlete development across multiple evaluation periods, would further strengthen the contributions of this work to the intersection of sports science and information systems.

DECLARATIONS

Author Contributions:

Pahrizal: Conceptualization, Methodology, Software, Validation, Data curation, Visualization, Writing–original draft. R Wisnu Prio Pamungkas: Supervision, Methodology, Validation, Writing–review & editing, Project administration. Fried Sinlae: Supervision, Investigation, Validation, Writing–review & editing. All authors have read and agreed to the final version of the manuscript.

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The data that support the findings of this study are available from the corresponding author upon reasonable request.

AI Use Statement:

The authors declare that the generative AI tool, Qwen, was utilized during the preparation and writing of this manuscript to assist in structuring the academic arguments, refining the language, and verifying the computational logic of the proposed system. The authors have thoroughly reviewed and edited the AI-assisted outputs and take full responsibility for the accuracy, integrity, and final content of the published article.

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