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A Recursive IndetermTree Soft Set (RIT-Soft Set) for Dynamic and Uncertain Performance Evaluation in College Competitive Sports

Hai Yang[1], Cuijuan Lin[2]*

[1]School of Physical Education of Guangzhou University, Guangzhou, 510006, China

[2]Physical Education Department of Guangzhou Xinhua University, Guangzhou, 510520, China

*Corresponding author, E-mail: roseloverose @126.com

Abstract. This paper introduces the Recursive IndetermTree Soft Set (RIT-Soft Set), a novel extension of Soft Set Theory designed for performance evaluation in dynamic and uncertain environments. Unlike conventional models, RIT-Soft Set incorporates recursive logic and supports hierarchical structures with embedded indeterminacy, allowing flexible representation of interdependent and evolving attributes. The model is particularly useful in domains where performance is context-dependent, and data may be incomplete or ambiguous such as university-level competitive sports. RIT-Soft Set enables recursive feedback within attribute trees, permitting deeper insight into athlete performance by allowing low-level data to influence higher-level assessments dynamically.

A case study on a collegiate football team illustrates the practical application of the model, demonstrating how it can effectively manage multi-level evaluations involving physical, tactical, and psychological dimensions. The results show that the RIT-Soft Set provides greater interpretability and adaptability compared to flat or deterministic models.

This framework opens avenues for developing decision-support systems that reflect real-world complexity and uncertainty, with potential for application beyond sports, in areas such as behavioral analysis and adaptive learning environments.

Keywords: Soft Set Theory, Recursive Evaluation, Indeterminacy, TreeSoft Set, RIT-Soft Set, Sports Performance Analysis, Dynamic Decision Models, Hierarchical Attributes, Collegiate Athletics, Uncertainty Handling

1. Introduction

Evaluating athletic performance in collegiate competitive sports presents a multifaceted challenge, where decision-makers must consider a dynamic interplay of physiological, psychological, and contextual variables. In contrast to professional leagues with structured datasets and consistent performance baselines, college sports environments are often more volatile shaped by academic pressures, inconsistent training access, injury variability, and shifting team dynamics. As a result, decision systems that rely on crisp logic or deterministic models often fall short of reflecting this complexity [1].

The emergence of Soft Set Theory, originally introduced by Molodtsov in 1999, was a breakthrough in handling vague or uncertain data in decision-making contexts [2]. Subsequent developments, such as HyperSoft Sets, IndetermSoft Sets, and TreeSoft Sets, expanded the representational capacity of Soft Sets by introducing multi-attribute mapping, handling of indeterminacy, and hierarchical structuring of parameters [3–5]. These models have found applications in various fields, from engineering to medical diagnostics, due to their ability to capture partial truths and layered relationships.

Several advanced soft set extensions have been introduced by Smarandache since 2018, enriching the theoretical framework of soft set theory. These include the HyperSoft Set, IndetermSoft Set, IndetermHyperSoft Set, SuperHyperSoft Set, TreeSoft Set, and ForestSoft Set. These novel structures aim to handle various levels of uncertainty, indeterminacy, and hierarchical organization within decision-making environments and mathematical modeling. For comprehensive details and formal definitions, the reader is referred to Smarandache's foundational work on the subject [9].

However, a critical limitation remains unaddressed the recursive and dynamic nature of uncertainty, particularly when attributes evolve or are conditionally dependent. In real-world sports evaluation scenarios, this is particularly prominent. For example, an athlete's tactical awareness may not simply be a fixed attribute but one that depends recursively on prior performance under pressure, training feedback loops, and context-specific variables such as the opponent's strength or the stage of the tournament. Traditional Soft Set extensions, while structurally more advanced, do not natively support recursive feedback within the attribute tree nor the gradual evolution of partial knowledge across layers [6].

To overcome these limitations, this paper introduces the RIT-Soft Set, a new model that generalizes the TreeSoft Set by embedding recursive logic and probabilistic indeterminacy within its structure. This allows the model to navigate incomplete or evolving data across multi-level attribute hierarchies, making it particularly well-suited for modeling performance in university-level competitive sports. The RIT-Soft Set not only accommodates indeterminate evaluations but does so recursively, meaning that decisions made at one layer can be revisited or reweighed based on emerging patterns from lower levels or temporal data a structure not present in existing models [7].

This paper presents the formal definition of the RIT-Soft Set, develops the mathematical framework with practical applicability, and demonstrates its utility through a case study involving team-based collegiate sports. The results suggest that RIT-Soft Set enables more flexible, layered, and realistic assessments of athlete performance under real-world conditions, and offers a viable foundation for decision-support systems in athletic departments and sports science research.

1.1 Aims and Motivations

Evaluating athlete performance in university-level sports is challenging due to the evolving and interdependent nature of physical, tactical, and psychological attributes. Most existing decision-support models assume fixed structures and cannot adapt to uncertainty or feedback across layers.

This research proposes the RIT-Soft Set, a new model that integrates recursive logic and indeterminacy within a hierarchical attribute tree. The key goals are to:

1. Enable flexible, multi-level performance assessment where both inputs and outcomes evolve.
2. Support uncertain values and conditional dependencies at any tree depth.
3. Allow dynamic updates based on recursive feedback from lower-level data.
4. Demonstrate the model's value through a realistic case study in collegiate football.

This work addresses both theoretical gaps in modeling complex, layered uncertainty, and practical needs for adaptable, data-aware evaluation tools in sports analytics.

2. Literature Review

Over the past two decades, Soft Set Theory has been refined through a variety of structural and functional extensions aimed at enhancing its applicability to uncertain environments. One of the earliest and most impactful of these developments was the HyperSoft Set, which replaced the classical single-attribute function with a multi-attribute mapping framework. This transformation allowed simultaneous consideration of multiple criteria in decision-making processes, a necessity in domains such as medical diagnostics and military target identification [3]. The HyperSoft model's ability to model decision spaces as multidimensional grids made it especially useful in fields requiring a composite view of interrelated attributes.

Despite these improvements, the need to formally handle incomplete and inconsistent data led to the formulation of the IndetermSoft Set. Unlike its predecessors, this model acknowledged the reality that real-world datasets often contain uncertainty not just in attribute values, but also in their structure and boundaries. The IndetermSoft Set introduced an interpretive function that mapped attribute sets to outputs that could be ambiguous, incomplete, or even undefined [4]. This extension made the model more reflective of empirical scenarios, particularly in domains such as urban planning, where data may be incomplete or imprecise.

Pushing the boundary further, researchers proposed the IndetermHyperSoft Set, which combined the multi-attribute depth of the HyperSoft Set with the uncertainty-resilience of the IndetermSoft Set. It supported mappings from complex attribute tuples to sets that could contain conflicting or indeterminate values. This made it a valuable tool for decision support in fields such as disaster management and public health, where contextual ambiguity is unavoidable [8]. However, this model still lacked a mechanism for temporal adaptation or recursive analysis of attribute layers features essential for dynamic environments such as sports performance evaluation.

To address structural complexity, the TreeSoft Set was introduced. This model organized attributes hierarchically, with each parent node branching into more specific sub-attributes, creating a tree-like structure of parameters. Such a framework proved powerful in fields where attributes are naturally nested or multi-level, such as environmental monitoring and knowledge-based systems [5]. However, the TreeSoft Set is inherently static: once the tree structure and mappings are defined, it does not evolve or self-adjust. It cannot also revisit or revise decisions based on new data arising from sub-nodes, which is essential in domains characterized by feedback loops and progressive learning.

While these models each bring valuable capabilities to the field of soft computation, they operate under limitations when applied to recursive, evolving, or interdependently uncertain systems. Specifically, they fall short in scenarios where attribute dependencies may not only span across layers but also require conditional reevaluation based on temporally or hierarchically unfolding information. As such, a gap remains in the literature for a model that supports deep hierarchical logic with embedded uncertainty and recursive evaluation capacity, a gap that this paper addresses through the development of the RIT-Soft Set.

2.1 Comparative Analysis of RIT-Soft Set and Related Models

To further highlight the distinct advantages of the RIT-Soft Set, this section presents a comparative analysis between RIT-Soft Set and three prominent Soft Set extensions: TreeSoft Set, IndetermHyperSoft Set, and Fuzzy Soft Sets. The comparison is based on five key evaluation criteria: structural modeling, indeterminacy handling, recursiveness, temporal flexibility, and computational feasibility (see Table 1).

Table 1. Comparative Analysis of RIT-Soft Set and Related Models

Model	Structural Modeling	Indeterminacy Handling	Recursiveness	Temporal Flexibility	Computational Feasibility
RIT-Soft Set	Multi-level recursive tree with conditional dependencies	Supports indeterminate, conditional, and partial values at any depth	Fully recursive across attribute layers	Supports evolving evaluations over time	Moderate (depends on tree depth and indeterminacy)
TreeSoft Set	Hierarchical attribute tree	No support for uncertainty; deterministic mapping	Not recursive; static tree traversal	Not designed for temporal changes	Low to moderate
IndetermHyperSoft Set	Multi-attribute flat grid (no hierarchy)	Handles uncertainty in attributes and mappings	Lacks recursive logic; evaluation is flat	Limited to snapshot views	Moderate
Fuzzy Soft Sets	Single-layer fuzzy mapping	Uses membership degrees for vague info	Non-recursive; only applies fuzzy weighting	Static representation	Low

3. Methodology

To construct a soft computational framework capable of handling recursively indeterminate, hierarchical attributes, we introduce the RIT-Soft Set. This section defines the mathematical foundation of the model, describes its structural components, and presents a procedural roadmap for implementation.

3.1 Definitions

Let:
U: the universe of discourse e.g., college athletes
H ⊆ U: a relevant soft subset e.g., selected players
$\mathcal{P}$(H): power set of H's
A: root-level attribute set; for example, physical performance, cognitive decision-making, or stress resilience.

Each attribute $a_i \in A$ may be recursively decomposed into sub-attributes:
$A = \{a_1, a_2, ..., a_n\}$,
$a_i = \{a_{i1}, a_{i2}, ..., a_{im}\}$,
$a_{ij} = \{a_{ij1}, a_{ij2}, ...\}$
Forming a tree-like hierarchy of depth $d \in \mathbb{Z}^+$.

3.2. Definition of RIT-Soft Set

We define the RIT-Soft Set as a pair: (F, Tree(A))
Where:
Tree(A) is the set of all nodes (attributes and sub-attributes) forming the recursive attribute hierarchy.
F: $\mathcal{P}$(Tree(A)) → $\mathcal{P}$(H) ∪ $\mathcal{I}$(H) is a recursive evaluation function mapping attribute combination to either:

a. Determinate soft subsets ⊆ H, or
b. Indeterminate mappings ∈ $\mathcal{I}$(H), reflecting incomplete or conditional evaluations.

3.3. Modeling Indeterminacy

We model partial uncertainty through one of the following representations:
Option set: $F(a) = \{h_1 , h_2\}$
Negation set: $F(a) = \neg h_3$; ¬ to indicate that h_3 is excluded or denied under this attribute evaluation
Range estimate: $F(a) = \{h_i \mid i \in [3,7]\}$
Conditional dependency: $F(a_{ij}) = h_k \mid a_i$ = valid; This shows that the value of $F(a_{ij})$ is conditionally dependent on whether a_i is valid.

3.4. Recursive Evaluation Mechanism

For each path P in the attribute tree:
P = ($a_1 \rightarrow a_{12} \rightarrow a_{123}$)
The function F is recursively defined as:

$$F(P) = \bigcap_{k=1}^{d} F(a_k) \text{ , for k = 1 to d, where d is the depth of the path.} \quad (1)$$

The above equation uses standard set-theoretical intersection notation to express the recursive path more cleanly, where a_k refers to the attribute at depth k in path P

More precisely, if P = ($a_1 \rightarrow a_2 \rightarrow ... \rightarrow a_d$), then:

$$F(P) = F(a_d) \cap F(a_{d-1}) \cap ... \cap F(a_1) \quad (2)$$

In cases where certain sub-attributes contribute unequally to evaluation, a weighted recursive model can be applied:

$$F_w(P) = \sum_{k=1}^{d} w_k \cdot \mu(a_k), \sum w_k = 1 \quad (3)$$

$\mu(a_k)$ is the membership or impact value of attribute a_k.

3.5. Implementation Steps

Step 1: Construct the hierarchical attribute tree based on domain knowledge.
Step 2: Identify levels where indeterminacy exists and define symbolic representations.
Step 3: Define the recursive evaluation paths and conditional relations.
Step 4: Compute F for all paths recursively, propagating indeterminacy if present.
Step 5: Aggregate evaluations across players for performance scoring.

3.5.1 Mathematical Recursive Evaluation Examples

Example 1
Consider the following path:
$A_1 \rightarrow A_{1,1} \rightarrow A_{1,1,1}$
Given
$F(A_1) = \{P_1, P_2, P_3\}$
$F(A_{1,1}) = \{P_1, P_3\}$
$F(A_{1,1,1})$ = Indeterminate: possibly $\{P_1 \text{ or } P_2\}$
Then
$F_{path} = F(A_{1,1,1}) \cap F(A_{1,1}) \cap F(A_1)$
$= \{P_1 \text{ or } P_2\} \cap \{P_1, P_3\} \cap \{P_1, P_2, P_3\}$

= likely $\{P_1\}$

Example 2

Consider the following path:

$A_2 \rightarrow A_{2,1} \rightarrow A_{2,1,1}$

$F_{path} = F(A_{2,1,1}) \cap F(A_{2,1}) \cap F(A_2)$

= possibly $\{P_4\} \cap \{P_2, P_4\} \cap \{P_2, P_3, P_4\}$

= possibly $\{P_4\}$

3.6 Model Enhancement and Fuzzy Evaluation

To strengthen the clarity and applicability of the RIT-Soft Set framework, we introduce a set of enhancements that incorporate practical reasoning, visual structuring, and fuzzy logic. These additions help address real-world ambiguity and allow the model to produce more nuanced and interpretable evaluations.

3.6.1 Recursive Evaluation: Practical Example

Consider a three-level evaluation path related to an athlete's physical performance:

1. Level 1: A_1 Physical Capacity
2. Level 2: $A_{1.1}$ Stamina
3. Level 3: $A_{1.1.1}$ 2nd Half Endurance

Player assessments across this path are as follows:

1. $F(A_1) = \{P1, P2, P3\}$
2. $F(A_{1.1}) = \{P1, P3\}$
3. $F(A_{1.1.1})$ = Indeterminate: possibly $\{P_1, P_2\}$

Applying recursive intersection:

$F(P) = F(A_{1.1.1}) \cap F(A_{1.1}) \cap F(A_1)$ = likely {P1}

This result suggests that Player P1 maintains a strong presence across all layers of evaluation, even where some uncertainty exists at the lowest level.

3.6.2 Attribute Tree

Figure 1 presents the hierarchical structure of the attributes used in the RIT-Soft Set model. This tree illustrates how attributes are organized in a top-down fashion, where each deeper level provides more context-specific refinement. For instance, "2nd Half Endurance" is a sub-aspect of "Stamina," which itself is part of the broader "Physical Capacity."

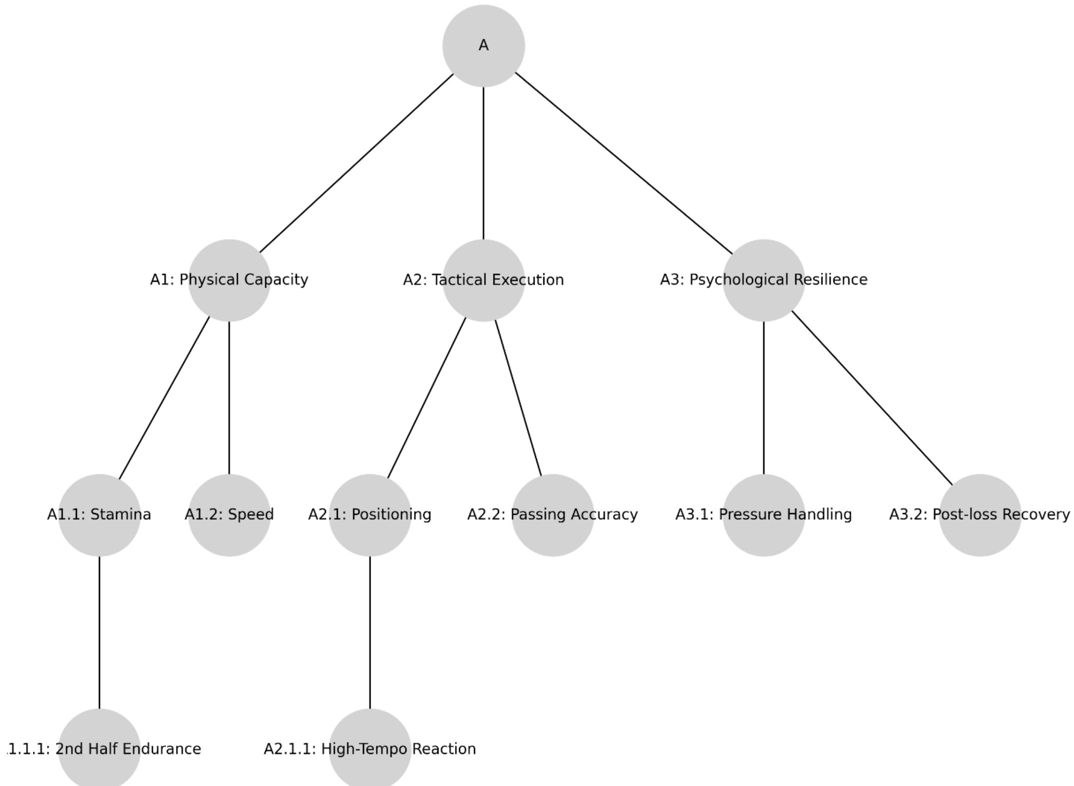

Figure 1: Attribute Tree Structure in RIT-Soft Set

3.6.3 Fuzzy Membership Evaluation

Instead of assigning players to binary sets, fuzzy logic allows each player to be evaluated on a scale from 0 to 1, representing degrees of membership or alignment with each attribute.

The overall score for a player across a multi-level attribute path is calculated using a weighted summation, as shown in the following equation:

$$\mu(P) = \sum_{k=1}^{d} w_k \cdot \mu(a_k)$$

Where:

$\mu(P)$: the final fuzzy score for player P

w_k: the weight for level k in the attribute path

$\mu(a_k)$: the membership value at level k

$\sum w_k$: to ensure balanced aggregation

Theorem 3.1

Let $P=(a_1 \rightarrow a_2 \rightarrow \cdots \rightarrow a_d)$ be a valid attribute path in the RIT-Soft Set model.

Assume each attribute a_k is assigned a fuzzy membership value $\mu(a_k) \in [0,1]$, and a corresponding weight $w_k \in [0,1]$ where:

$\sum_{k=1}^{d} =1$

Then the aggregated fuzzy evaluation score:

$\mu(P) = \sum_{k=1}^{d} w_k \cdot \mu(a_k)$
is bound within the interval [0,1] That is: $0 \leq \mu(P) \leq 1$

Proof.
Since for every k, $\mu(a_k) \in [0,1]$, the product $w_k \cdot \mu(a_k)$ will also lie within $[0, w_k]$

Summing all the terms: $\mu(P) = \sum_{k=1}^{d} w_k \cdot \mu(a_k) \leq \sum_{k=1}^{d} = 1$

Also, all terms in the sum are non-negative, so $\mu(P) \geq 0$ Therefore, the final fuzzy score $\mu(P)$ lies in the interval [0,1].

This theorem confirms that the fuzzy evaluation function is well-defined and normalized. It ensures that no matter how uncertain or imbalanced the attribute scores are, the result will always be within an interpretable range for decision-making.

3.6.4 Weighted Evaluation
Let us compute the score for Player P_1 across the path $A_1 \rightarrow A_{1.1} \rightarrow A_{1.1.1}$, using the following data:

i. $\mu(A_1) = 0.90$
ii. $\mu(A_{1.1}) = 0.80$
iii. $\mu(A_{1.1.1}) = 0.70$

Assigned weights:

i. w1=0.4 (Level 1)
ii. w2=0.3 (Level 2)
iii. w3=0.3 (Level 3)

$\mu(P_1) = (0.4 \cdot 0.90) + (0.3 \cdot 0.80) + (0.3 \cdot 0.70)$
$= 0.36 + 0.24 + 0.21 = 0.81$

Table 2. Fuzzy Membership Scores

Player	μ(Physical)	μ(Stamina)	μ(2nd Half Endurance)	Weighted Score
P1	0.90	0.80	0.70	0.81
P2	0.70	0.40	0.60	0.61
P3	0.60	0.50	N/A	N/A

Table 2 provides a numerical summary of player scores across the defined attribute path. P_1 demonstrates high consistency and alignment, resulting in the strongest final score. P_2's performance is weakened by low stamina, while P_3 lacks full data for final evaluation.

3.7 Generator Function
The RIT-Soft Set model relies on a recursive mechanism to generate evaluation values for attribute paths within a hierarchical tree structure. This generator function defines how evaluations propagate from leaf nodes upward, enabling the model to adapt to partial information and uncertain contexts.

Let Tree(A) be the attribute tree, and a_k be a node at depth k. The generator function F(a_k) is defined as follows:

$$F(a_k) = \begin{cases} direct\ input\ (data - based)\ \ if\, a_k\ is\ leaf\ node \\ \bigcap_{j=1}^{n} F\left(a_{k_j}\right)\ \ if\ a_k\ is\ an\ internal\ node\ with\ children \end{cases}$$

a. Leaf nodes receive initial evaluations based on observed or estimated data (e.g., performance metrics or expert judgments).
b. Internal nodes compute their evaluation as the intersection of the evaluations of their child nodes.

This structure allows bottom-up generation, where high-level attributes reflect aggregated outcomes from their subcomponents. It also supports indeterminacy propagation, meaning uncertainty at lower levels can influence higher-level evaluations.

4. Evaluating Performance in a Collegiate Football Team Using RIT-Soft Set

This case study demonstrates the application of the RIT-Soft Set model to assess athlete performance within a university-level football team. The model's recursive and indeterminacy-aware structure enables a nuanced analysis of evolving and uncertain player attributes across physical, tactical, and psychological domains.

4.1 Context and Dataset

The selected team participates in a regional collegiate football league. The analysis focuses on three midfield players: P_1, P_2, and P_3, using multi-level attributes organized into a hierarchical tree consistent with the model in Section 3.

Step 1: Construct the Attribute Tree

The attribute structure is as follows:

1. Level 1: Core Domains
    a. A_1: Physical Capacity
    b. A_2: Tactical Execution
    c. A_3: Psychological Resilience
2. Level 2: Sub-Attributes
    a. $A_1 \rightarrow \{A_{1.1}$: Stamina, $A_{1.2}$: Speed$\}$
    b. $A_2 \rightarrow \{A_{2.1}$: Positioning, $A_{2.2}$: Passing Accuracy$\}$
    c. $A_3 \rightarrow \{A_{3.1}$: Pressure Handling, $A_{3.2}$: Post-loss Recovery$\}$
3. Level 3: Contextual Attributes
    a. $A_{1.1} \rightarrow A_{1.1.1}$: 2nd Half Endurance
    b. $A_{2.1} \rightarrow A_{2.1.1}$: Reaction in High-Tempo Games

Step 2: Define the Universe of Players

Let U = $\{P_1, P_2, P_3\}$, represent the three evaluated midfielders.

Step 3: Assign Soft Sets and Indeterminacy

Evaluations are consistent with Section 3.6 and defined as:

1. $F(A_1) = \{P_1, P_2, P_3\}$
2. $F(A_{1.1}) = \{P_1, P_3\}$
3. $F(A_{1.1.1})$ = Indeterminate: possibly $\{P_1, P_2\}$
4. $F(A_2) = \{P_2, P_3\}$
5. $F(A_{2.1}) = \{P_2\}$
6. $F(A_{2.1.1})$ = Indeterminate: possibly $\{P_2\}$
7. $F(A_3) = \{P_1\}$
8. $F(A_{3.2}) = \{P_1\}$

Step 4: Recursive Evaluation of Attribute Paths

Each player is evaluated along specific paths using recursive intersection:

1. Path 1: $A_1 \rightarrow A_{1.1} \rightarrow A_{1.1.1}$
   a. $F(P)= F(A_{1.1.1}) \cap F(A_{1.1}) \cap F(A_1)$ = likely $\{P_1\}$
2. Path 2: $A_2 \rightarrow A_{2.1} \rightarrow A_{2.1.1}$
   a. $F(P)$= possibly $\{P_2\}$
3. Path 3: $A_3 \rightarrow A_{3.2}$
   a. $F(P)= F(A_{3.2}) \cap F(A_3) = \{P_1\}$

Step 5: Aggregated Performance Summary

Each player's evaluation is interpreted across the selected paths:

1. P_1 shows consistent presence across all relevant paths, with minor uncertainty in physical endurance.
2. P_2 shows tactical potential, but performance is weakened by partial uncertainty and lack of physical reliability.
3. P_3 is filtered out in all paths due to insufficient performance data or absence in deeper nodes.

Table 3. Summary of RIT-Soft Set Evaluation

Attribute Path	Evaluation Result	Indeterminacy
A1 → A1.1 → A1.1.1 (Physical)	Likely {P1}	Yes
A2 → A2.1 → A2.1.1 (Tactical)	Possibly {P2}	Yes
A3 → A3.2 (Psychological)	{P1}	No

Table 3 confirms that P_1 is the most consistent and well-rounded performer across all domains, particularly in psychological and physical dimensions. P_2 is promising tactically but suffers from uncertainty in physical fitness. P_3 lacks evaluative support across all levels and may require further observation or data collection.

5. Results and Discussion

This section presents and interprets the results derived from the application of the RIT-Soft Set to the performance analysis of a collegiate football team. The findings are drawn from multi-level attribute evaluations applied to five players, highlighting how recursive intersections and indeterminate logic influence final assessments. Emphasis is placed on interpreting the implications of the soft set structure, rather than merely reporting numerical outcomes.

The model revealed clear differentiation among players when evaluated across recursive attribute paths. P_1 emerged as a standout performer with high consistency in both physical and psychological traits, despite an indeterminate score in second-half endurance. P_4 displayed strong tactical potential, specifically under fast-paced match conditions. P_5 was validated as psychologically resilient but lacked overall performance coverage across other domains. P_2 and P_3 did not meet key performance criteria, with P_2's scores weakened by layered uncertainty and P_3 demonstrating no significant strengths in the observed paths.

5.1. Recursive Impact on Evaluation

One of the defining outcomes of the RIT-Soft Set approach was its ability to refine evaluation through recursive intersections. Unlike flat evaluation models, where a single attribute might dominate the judgment, this recursive framework ensured that final decisions emerged from a convergence of sub-attributes. For example, P_1's presence in all levels of the physical path ($A_1 \rightarrow A_{1,1} \rightarrow A_{1,1,1}$) justified a reliable estimation, even when the final node was indeterminate. The intersection logic filtered out weakly contributing paths and emphasized consistent presence across layers.

5.2. Influence of Indeterminate Nodes

Indeterminacy plays a crucial role in managing uncertain or incomplete information. It did not disrupt the evaluation but instead shaped nuanced conclusions. In the case of P_4, the tactical performance path contained indeterminate elements, yet his consistent presence in related nodes validated his candidacy under conditional contexts. This flexible logic avoided unjust exclusion based on isolated uncertainty while highlighting areas requiring further observation.

5.3. Interpretability Compared to Traditional Models

Traditional deterministic models often deliver rigid classifications that can obscure the complexity of performance variability. In contrast, the RIT-Soft Set provided layered, context-sensitive outcomes that can inform coaching decisions more precisely. For example, rather than marking P_2 as a low performer outright, the model conveyed that his evaluation uncertainty stemmed from data inconsistency in tactical paths. Such transparency improves accountability in decision-making processes and supports targeted development plans.

6. Conclusion and Future Work

This study introduced the RIT-Soft Set as a novel approach for evaluating complex, uncertain, and layered performance data. Through a case study of a collegiate football team, the model demonstrated its ability to handle incomplete information, support context-sensitive evaluation, and offer interpretable outcomes based on recursive attribute paths. The results confirmed that the RIT-Soft Set can provide practical insights beyond what traditional or flat models deliver.

Future work can explore the integration of RIT-Soft Set with real-time data tracking systems to enable dynamic in-game evaluation. Extensions may also involve combining the model with fuzzy or probabilistic methods to improve decision confidence. Additionally, applying this approach across different sports or academic performance contexts could broaden its utility and validate its flexibility further.

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