

# Can Semantic Methods Enhance Team Sports Tactics? A Methodology for Football with Broader Applications

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## Abstract

This paper explores how semantic-space reasoning, traditionally used in computational linguistics, can be extended to tactical decision-making in team sports. Building on the analogy between *texts* and *teams*—where players act as words and collective play conveys meaning—the proposed methodology models tactical configurations as compositional semantic structures. Each player is represented as a multidimensional vector integrating technical, physical, and psychological attributes; team profiles are aggregated through contextual weighting into a higher-level semantic representation.

Within this shared vector space, tactical templates such as *high press*, *counterattack*, or *possession build-up* are encoded analogously to linguistic concepts. Their alignment with team profiles is evaluated using vector-distance metrics, enabling the computation of tactical “fit” and opponent-exploitation potential. A Python-based prototype demonstrates how these methods can generate interpretable, dynamically adaptive strategy recommendations, accompanied by fine-grained diagnostic insights at the attribute level.

Beyond football, the approach offers a generalizable framework for collective decision-making and performance optimization in team-based domains—ranging from basketball and hockey to cooperative robotics and human–AI coordination systems. The paper concludes by outlining future directions toward real-world data integration, predictive simulation, and hybrid human–machine tactical intelligence.

**Keywords:** semantic distance; decision support systems; recommender systems; sports analytics; tactical optimization; human–artificial integration

## 1 Introduction

Modern football has undergone a radical transformation, evolving from a discipline grounded mainly in coaches’ intuition and experience into one profoundly shaped by objective data analysis. The widespread adoption of advanced analytics systems, proprietary metrics such as expected goals (xG) and expected assists (xA), and the availability of detailed information on players’ physical, technical, and tactical performance have enabled a quantitative understanding of phenomena once accessible only through human judgment [19].

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In this data-driven landscape, **tactical optimization**—the ability to select and dynamically adjust playing strategies according to the team’s internal characteristics and the contingent match conditions—has become a decisive competitive factor. At elite levels, marginal advantages can determine the outcome of an entire season. Tactical effectiveness no longer depends solely on individual talent or preparation quality but also on the ability to interpret complex contexts, anticipate opponents’ actions, and adapt strategies in real time. However, traditional decision models based primarily on qualitative heuristics and experience reach their limits when faced with the high dimensionality and dynamism of modern play [14, 23].

Despite significant progress in match analysis, a structural discontinuity persists between **quantitative analytical tools**—such as numerical performance indicators, spatial distributions, or xG-based predictive models—and **qualitative contextual factors** that critically influence collective performance. These include group cohesion, psychological resilience, team morale, residual energy, and the quality of tactical leadership [15, 28]. Current decision support systems (DSS) tend to emphasize easily measurable variables (e.g., physical metrics) while neglecting intangible dimensions that often prove decisive in dynamic, high-pressure contexts. This gap results in: (i) loss of strategically relevant information; (ii) limited adaptability and personalization of recommendations; and (iii) persistent reliance on subjective intuition in crucial phases of play [21].

To address these challenges, the present study introduces a **Decision Support System for Tactical Optimization** grounded in an innovative **semantic-distance methodology**. The key idea is to represent, within a common vector space, both the team’s contextual configuration — aggregating technical, physical, psychological, and organizational attributes — and the ideal profiles of canonical tactical strategies (e.g., high pressing, counterattack, possession build-up). The system then recommends the most coherent strategy by minimizing the semantic distance (computed via cosine and Euclidean metrics) between these two sets of vectors. This approach enables transparent integration of quantitative data and expert knowledge, allowing dynamic adaptation to evolving match contexts (e.g., changes in collective energy or morale).

A distinctive feature of this research lies in the **transfer of a general semantic methodology**—conceived initially to bridge analytical frameworks and decision heuristics—to the particular tactical domain of football. In the reference paper *Recommending Actionable Strategies* [5], semantic distance was used to connect abstract structures (such as the 6C model) with historical heuristic systems (like the Thirty-Six Stratagems), demonstrating the potential to mediate between conceptual traditions.

The present work extends this paradigm to the operational level of **tactical practice**, replacing:

- general decision categories with 14 concrete **macro-attributes** capturing technical, psychological, and organizational dimensions of a team; and
- general heuristics with a structured repertoire of **canonical football strategies** (e.g., high pressing, counterattack, positional defense).

Thus, the contribution goes beyond replication, applying semantic modeling to the tactical decision-making process to produce contextual, interpretable, and immediately actionable recommendations for coaching staff. This transposition—from general semantic theory to applied sports intelligence—represents the main innovative contribution of the work, aligning with the interdisciplinary research frontier that integrates **NLP, decision theory, and sports science**.

The main contributions of this research can be summarized as follows:

1. **Formalization of an Integrated Semantic Model for Football** – Adaptation and extension of the *Recommending Actionable Strategies* methodology to the football domain, defining 14 multidimensional macro-attributes that synthesize a team’s complexity (including Offensive Strength, Psychological Resilience, and Tactical Cohesion).

2. **Development of a Tactical Recommender Prototype** – Implementation, in Python, of a recommendation engine capable of aggregating heterogeneous data and comparing them against predefined tactical models. The prototype includes dynamic weighting mechanisms to adjust recommendations in real time (e.g., penalizing energy-intensive strategies when residual stamina is low).
3. **Systematic Evaluation and Robustness Testing** – Validation through both simulated scenarios (Advantage/Draw/Disadvantage  $\times$  High/Low Energy) and retrospective analysis of real match data from German youth football. The evaluation includes ablation studies and robustness-to-noise analyses, ensuring the model’s interpretability and consistency across synthetic and empirical conditions.

In summary, this work contributes to the ongoing digital transformation of football by proposing an interpretable, flexible, and data-driven approach to tactical decision support that bridges the gap between numerical analytics and expert knowledge and lays the foundations for next-generation adaptive strategy systems.

The remainder of this paper is organized as follows. Section 2 reviews related work on performance analysis, decision support systems in sports, and semantic similarity methods. Section 3 presents the proposed methodology, including the formalization of the semantic model, the definition of macro-attributes, and the recommendation mechanism. Section 4 describes the prototype implementation in Python. Section 5 reports the experimental evaluation based on simulated scenarios, including ablation and robustness analyses. Section 6 extends the validation to real match data through retrospective case studies. Section 7 discusses the results, limitations, and practical implications. Finally, Section 8 concludes the paper and outlines directions for future work.

## 2 Background and Related Work

The introductory section highlighted the need to bridge the gap between quantitative analytics and heuristic decision-making in football. To formalize the proposed solution, it is first necessary to establish a solid conceptual foundation that clarifies the distinction between *strategy* and *tactics*, and then to situate this distinction within the broader context of semantic modeling and decision-support research.

### 2.1 Strategic and Tactical Analysis in Football

In everyday football discourse, the terms *strategy* and *tactics* are often used interchangeably. However, in the academic and analytical literature, they refer to distinct levels of decision-making that are crucial to our methodology.

**Strategy** (or playing identity) defines the overall approach or long-term plan through which a team intends to compete. It depends on structural and contextual factors such as squad quality, key players’ technical and physical profiles, seasonal goals, the coach’s philosophy, and the team’s physical and psychological resources [8, 15]. Strategy answers the question: *What do we want to achieve?*—for example, controlling the game through ball possession.

**Tactics**, in contrast, represent the operational choices and on-field configurations that translate strategy into concrete actions, often in response to real-time match dynamics. They include formation choices, player assignments, coordinated movements (e.g., defensive shifts), and in-game adaptations such as introducing an additional forward when chasing a result. Tactics answer the question: *How do we achieve it?*

This distinction is central to the proposed **Decision Support System (DSS)**. The system operates at the tactical level—optimizing action choices based on a multidimensional strategic representation of the team. The semantic-distance model quantifies the alignment between:

1. the *strategic vector* of the team (its current state, defined by 14 macro-attributes), and
2. the *ideal tactical vector* (the target profile of a given strategy, such as counterattack or high pressing).

A correct balance between strategic identity and tactical flexibility ensures internal coherence. Teams with strong strategic identity but low adaptability become predictable and fragile, while excessive tactical improvisation undermines structural stability and collective performance [10].

## 2.2 Canonical Tactical Strategies in Modern Football

The following tactical archetypes comprise the conceptual foundation of our vector modeling framework. For each, the team attributes required for effective implementation are indicated.

**High Pressing.** A proactive approach aimed at regaining possession in the opponent’s half by applying intense, coordinated pressure. It reduces opponents’ time and space, forcing errors and enabling rapid goal opportunities [1, 2, 13]. It requires exceptional physical conditioning, coordination, and risk tolerance.

**Counterattack (Rapid Transition).** Based on defending in a compact mid-low block to lure the opponent forward, then striking rapidly upon regaining possession. It exploits spaces behind the defense and requires speed, verticality, and sharp decision-making.

**Positional Defense.** A space-oriented approach emphasizing spatial control over immediate pressure. Spatio-temporal analysis methods have been developed to quantify team coordination and territorial control [9]. Positional defense prioritizes equilibrium, communication, and tactical discipline while conserving energy [4].

**Gegenpressing (Pressing After Loss).** An aggressive evolution of pressing, aiming to recover the ball within 3–5 seconds after losing it by exploiting the opponent’s temporary disorganization. Extremely demanding, it requires maximal energy, readiness, and synchronization.

**Build-up Play.** A possession-based approach initiating offensive buildup from the back through short passes and gradual progression, designed to control tempo and overcome pressure via numerical superiority [26]. It requires technically skilled players across all lines, especially defenders and goalkeepers, who can distribute the ball.

These archetypes serve as idealized templates within our system, allowing the computational comparison of a team’s actual state with prototypical tactical profiles.

## 2.3 Semantic Distance Models

**Semantic distance** provides a quantitative measure of how far two informational entities—concepts, documents, or representations—differ in meaning when embedded in a shared vector space. In natural language processing (NLP), such models rest on the principle that numerical representations of linguistic units capture latent semantic relations, enabling mathematical comparison across heterogeneous content [16, 27].

Classical approaches include:

- **Cosine similarity**, which measures the angle between normalized vectors, robust to scale differences;
- **Euclidean distance**, which quantifies geometric deviation in continuous space;
- **Probabilistic metrics**, such as Kullback–Leibler [11] or Jensen–Shannon [12] divergences, used when entities are modeled as probability distributions.

<sup>4</sup>With the advent of Transformer architectures (e.g., BERT, RoBERTa, Sentence-BERT) [3, 20], Contextual embeddings have dramatically improved representation quality, dynamically

capturing meaning and outperforming static models such as Word2Vec and GloVe. These techniques have been widely adopted in information retrieval, question answering, text classification, and recommender systems [25].

In the reference paper *Recommending Actionable Strategies* [5], semantic distance was used to integrate two historically distinct traditions in strategy theory:

1. structured analytical frameworks (e.g., SWOT, 6C), and
2. decision heuristics (e.g., the Thirty-Six Stratagems).

Both were projected into a shared semantic space, enabling the computation of similarity matrices that link structured analysis to heuristic insight. This pipeline demonstrated how semantic methods can act as an interpretive bridge between abstract models and actionable guidance.

The present research adapts that paradigm to the football domain, replacing general analytical categories with 14 football-specific macro-attributes (e.g., Offensive Strength, Tactical Cohesion, Psychological Resilience) and general heuristics with canonical tactical strategies. The optimal tactical choice  $S^*$  is thus defined as the strategy minimizing the semantic distance  $d(V_{\text{team}}, V_{\text{strategy}}(S))$  between the team's current vector representation and the target tactical profile:

$$S^* = \arg \min_S d(V_{\text{team}}, V_{\text{strategy}}(S)).$$

## 2.4 Decision Support Systems in Sports

**Decision Support Systems (DSS)** are computational tools designed to assist coaches, analysts, and managers in complex decision-making by integrating quantitative data, expert knowledge, and predictive modeling capabilities. The increasing availability of high-resolution data—from GPS tracking, wearable sensors, and video-analysis platforms—has fostered the development of DSS capable of transforming information into operational insight [21, 22].

Across sports, DSS applications range from performance optimization to injury prevention and tactical planning:

- **Athletics and individual sports**—systems such as Catapult AMS or Kitman Labs monitor fatigue and workload by combining physiological and subjective data;
- **Basketball and team sports**—platforms like Synergy Sports and Second Spectrum merge positional tracking with video analytics to identify offensive and defensive patterns [7];
- **Cycling and endurance disciplines**—predictive tools such as Performance Management Charts use power and heart-rate data to optimize training loads.

In football, systems like **Wyscout** and **InStat** provide video-based statistical analytics; **StatsBomb IQ** integrates positional and event data into advanced metrics (e.g., xG, passing networks); **SciSports Insight** uses AI-based indices for player recruitment and compatibility analysis; and **SkillCorner** applies computer vision to extract player trajectories in real time [18].

While these systems have expanded analytical capabilities, most focus on quantitative or spatial data, overlooking qualitative and psychological aspects such as morale, cohesion, and resilience. Moreover, strategic recommendations often rely on expert interpretation rather than automated reasoning. The present work addresses this methodological gap by introducing a semantic-distance-based DSS that integrates multidimensional, context-aware modeling—combining quantitative metrics and tacit knowledge into a unified, interpretable framework.

### 3 Methodology

#### 3.1 Theoretical Framework

We adapt the methodology of *Recommending Actionable Strategies* [5] to the football domain, aiming to build a tactical recommender that integrates a team’s technical, organizational, and psychological dimensions within a shared semantic space. The core idea is to encode both (i) the contextual state of a team and (ii) the ideal profiles of canonical tactical strategies in the same vector space, and then to select the tactic whose profile is closest (in a semantic–geometric sense) to the team’s current state. Recommendations can be updated dynamically as match conditions evolve (e.g., residual energy, technical/physical gaps, time pressure).

Three pillars characterize this approach:

1. **Multidimensional integration** of quantitative (individual and collective performance) and qualitative (morale, cohesion, psychological resilience) factors.
2. **Semantic formalization** via normalized vectors in a common space, enabling consistent comparisons between teams and tactics.
3. **Dynamic adaptability** through real-time reweighting of distances using match conditions.

#### 3.2 Context Tree and Aggregation

We represent team context with a hierarchical *context tree* that aggregates heterogeneous data sources into a unified vector representation. The tree has three levels:

1. **Leaf level:** Raw observables from match analytics—player-level metrics from event data (passes, shots, tackles), tracking data (sprint distance, positioning), and physiological monitoring (heart rate, estimated fatigue).
2. **Intermediate level:** Role-aggregated attributes computed by combining leaf-level data within positional groups (e.g., “forward line offensive output,” “midfield ball retention”).
3. **Root level:** The 14 macro-attributes ( $A_1, \dots, A_{14}$ ) that define the shared semantic space, computed by weighted combination of intermediate-level signals.

Figure 1 illustrates this hierarchical structure for a subset of attributes.

**Aggregation Example.** To illustrate the aggregation process concretely, consider how  $A_1$  (Offensive Strength) is computed for a team fielding a 4-3-3 formation:

1. **Leaf level:** Extract per-player metrics—e.g., Striker A:  $xG = 0.82$ , shot accuracy = 0.71; Winger B:  $xA = 0.65$ , successful dribbles = 0.78.
2. **Intermediate level:** Aggregate within positional groups using role-based weights:

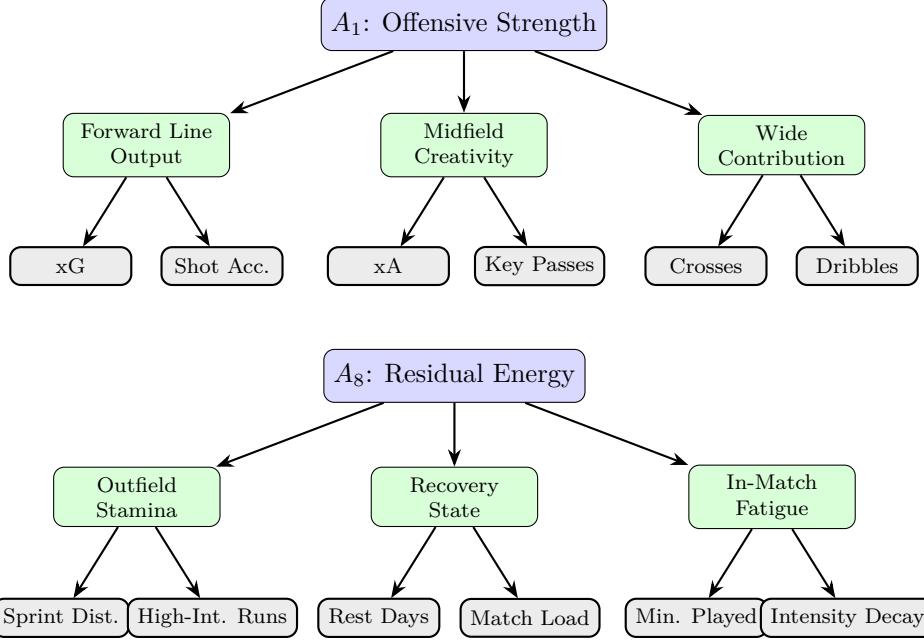
$$\text{Forward Output} = 0.5 \times xG_{\text{ST}} + 0.3 \times \text{ShotAcc}_{\text{ST}} + 0.2 \times xG_{\text{wings}}$$

$$\text{Midfield Creativity} = 0.6 \times xA_{\text{CAM}} + 0.4 \times \text{KeyPasses}_{\text{CM}}$$

3. **Root level:** Combine intermediate values into the macro-attribute:

$$A_1 = 0.50 \times \text{Forward Output} + 0.30 \times \text{Midfield Creativity} + 0.20 \times \text{Wide Contribution}$$

All intermediate and final values are normalized to  $[0, 1]$  via min-max scaling against league or historical benchmarks, ensuring cross-team comparability.



**Figure 1:** Context tree structure for two representative macro-attributes. Leaf nodes contain raw observables from match data; intermediate nodes aggregate by functional role; root nodes are the macro-attributes used in semantic distance computation. Edges represent weighted aggregation functions.

**Data Sources.** The context tree is designed to integrate multiple data streams:

- **Event data** (e.g., Opta, StatsBomb): passes, shots, tackles, interceptions → technical attributes ( $A_1$ – $A_6$ ,  $A_{11}$ ,  $A_{12}$ )
- **Tracking data** (e.g., SkillCorner, Second Spectrum): positions, velocities, distances → physical attributes ( $A_4$ ,  $A_8$ ,  $A_{13}$ )
- **Physiological monitoring** (e.g., Catapult, Polar): heart rate, workload → energy and fatigue ( $A_8$ )
- **Qualitative assessments**: coach ratings, historical stability → psychological/organizational attributes ( $A_7$ ,  $A_9$ ,  $A_{14}$ )

This modular design allows the system to operate with varying data availability—from fully instrumented professional environments to amateur contexts where only basic event data exists.

### 3.3 A Shared Semantic Space: 14 Macro-Attributes

The shared vector space is spanned by 14 macro-attributes,  $A_1, \dots, A_{14}$ , each normalized to  $[0, 1]$  and computed via the context tree aggregation described above. This unified representation enables three core operations:

1. **Team state encoding:** Describe a team’s contextual state at time  $t$  as a vector  $V_{\text{team}} \in [0, 1]^{14}$ .
2. **Strategy profiling:** Encode the ideal requirements of a tactical strategy as  $V_{\text{strategy}} \in [0, 1]^{14}$ .
3. **Semantic matching:** Compute distance  $d(V_{\text{team}}, V_{\text{strategy}})$  to identify the best-aligned tactic.

This tripartite structure ensures that tactical recommendations account not only for technical fit but also for physical sustainability and psychological readiness—dimensions often overlooked in purely statistical approaches.

**Attribute Categories and Design Rationale.** The set of 14 attributes was designed to balance the following three design criteria, with Table 1 providing their complete specification:

- **Technical/Tactical** ( $A_1$ – $A_6$ ): On-field performance capabilities—what the team can *do*.
- **Physical** ( $A_8$ ,  $A_{12}$ ,  $A_{13}$ ): Athletic resources and current energy state—what the team can *sustain*.
- **Psychological/Organizational** ( $A_7$ ,  $A_9$ ,  $A_{10}$ ,  $A_{11}$ ,  $A_{14}$ ): Intangible factors affecting collective performance—how the team *responds* under pressure.

**Aggregation Functions.** Leaf-level player attributes are aggregated to team-level macro-attributes through weighted combination functions. The general form is:

$$A_j = \sum_{i=1}^n w_{ij} \cdot a_{ij}, \quad \text{where } \sum_{i=1}^n w_{ij} = 1 \quad (1)$$

where  $a_{ij}$  represents player  $i$ 's contribution to attribute  $j$ , and  $w_{ij}$  is a role-based weight (e.g., forwards contribute more heavily to  $A_1$ ; defenders to  $A_2$ ). Specific aggregation formulas are documented in the prototype implementation (see Section 5.6).

**Dynamic vs. Static Attributes.** Some attributes vary during a match (dynamic), while others remain relatively stable (static):

- **Dynamic:**  $A_8$  (Residual Energy),  $A_9$  (Team Morale),  $A_7$  (Psychological Resilience under match stress)
- **Static:**  $A_{12}$  (Technical Base),  $A_{13}$  (Physical Base),  $A_{14}$  (Relational Cohesion)
- **Context-dependent:**  $A_5$  (High Press Capability depends on energy),  $A_{10}$  (Time Management becomes critical late in matches)

This distinction informs the dynamic reweighting mechanism (Section 3.5), which adjusts attribute salience in response to evolving match conditions.

### 3.4 Encoding Tactical Strategies as Vectors

A key methodological contribution of this work is the formalization of tactical strategies as vectors in the same semantic space defined by the 14 macro-attributes. This representation enables direct, quantitative comparison between a team's current state and the requirements of candidate strategies, transforming qualitative tactical concepts into computationally tractable objects.

**Table 1:** Complete specification of the 14 macro-attributes defining the shared semantic space.

ID	Attribute Name	Definition & Aggregation Source
<i>Technical/Tactical Dimensions</i>		
$A_1$	Offensive Strength	Capacity to create and convert goal-scoring opportunities. Aggregated from forwards' and midfielders' xG, dribbling success, and shot accuracy.
$A_2$	Defensive Strength	Ability to prevent opponent attacks and protect the goal. Derived from defenders' tackling, interceptions, aerial duels, and goalkeeper reflexes.
$A_3$	Midfield Control	Dominance in central zones and ability to dictate tempo. Based on central midfielders' passing accuracy, interceptions, and ball retention.
$A_4$	Transition Speed	Capability for rapid phase changes between defense and attack. Computed from speed attributes of forwards, fullbacks, and midfielders, combined with xA.
$A_5$	High Press Capability	Aptitude for coordinated pressing in advanced zones. Aggregated from stamina, aggression, and interception rates across all outfield players.
$A_6$	Width Utilization	Effectiveness in exploiting wide areas of the pitch. Derived from fullbacks' and wingers' crossing, dribbling, and speed attributes.
<i>Physical Dimensions</i>		
$A_8$	Residual Energy	Current stamina reserves across the squad. Computed from stamina values weighted by playing time, with resilience as a moderating factor.
$A_{12}$	Technical Base	Overall technical quality of the squad. Mean of technical attributes (passing, dribbling, first touch, xG, xA) across all players.
$A_{13}$	Physical Base	Overall athletic capacity of the squad. Mean of physical attributes (speed, stamina, aerial ability, aggression) across all players.
<i>Psychological/Organizational Dimensions</i>		
$A_7$	Psychological Resilience	Mental toughness and ability to perform under pressure. Weighted combination of individual resilience and aggression attributes.
$A_9$	Team Morale	Collective motivation and positive emotional state. Derived from resilience and aggression, modulated by match context (score, momentum).
$A_{10}$	Time Management	Ability to adapt tactics to match clock pressure. Based on experienced players' (GK, CM, FB) interception and passing attributes.
$A_{11}$	Tactical Cohesion	Synchronization and coordination between team units. Computed from passing networks, xA distribution, and positional discipline.
$A_{14}$	Relational Cohesion	Stability of internal relationships and group dynamics. Estimated via qualitative assessment or historical team stability indicators.

### 3.4.1 Strategy Vector Definition

Each canonical strategy  $S_i$  is represented as an *ideal profile vector*:

$$V_{\text{strategy}}^{(i)} = [s_i^{A_1}, s_i^{A_2}, \dots, s_i^{A_{14}}], \quad s_i^{A_j} \in [0, 1] \quad (2)$$

where  $s_i^{A_j}$  represents the importance or requirement level of attribute  $A_j$  for strategy  $S_i$ . A value of 0 indicates the attribute is irrelevant to the strategy; a value of 1 indicates it is critically important.

This formulation treats strategies not as binary labels but as *continuous profiles* that specify the ideal team characteristics for effective implementation. The semantic distance between a team vector  $V_{\text{team}}$  and a strategy vector  $V_{\text{strategy}}^{(i)}$  thus quantifies the “fit” between the team’s current capabilities and the strategy’s demands.

### 3.4.2 Construction Methodology

Strategy vectors were constructed through a four-stage process combining expert knowledge, tactical literature, and empirical validation:

**Stage 1: Strategy Selection.** Twenty canonical strategies were selected based on three criteria:

- (a) **Prevalence:** Strategies commonly employed in modern professional football, as documented in tactical analysis literature and match reports.
- (b) **Diversity:** Coverage of the tactical spectrum from ultra-defensive (e.g., deep block) to ultra-offensive (e.g., high pressing), and from possession-based to direct approaches.
- (c) **Distinctiveness:** Strategies with clearly differentiated attribute profiles, ensuring meaningful separation in the semantic space.

The selected strategies span five functional categories:

- *Offensive systems:* Build-up play, direct vertical attack, systematic crossing, overlapping flanks, delayed midfielder runs
- *Pressing variants:* High pressing, gegenpressing, midfield pressing, inducing build-up errors
- *Defensive structures:* Positional defense, deep block, compact zonal defense, strict man-marking, offside trap
- *Transition-based:* Fast counterattack, long ball to target man
- *Possession/control:* Extended possession play, cautious horizontal circulation, central block with quick breaks

**Stage 2: Qualitative Mapping.** For each strategy, tactical requirements were mapped onto the 14 macro-attributes using three sources:

- (a) **Tactical literature:** Coaching manuals, academic analyses of playing styles, and documented tactical frameworks.
- (b) **Match analysis:** Review of professional matches where strategies were explicitly employed, noting observable attribute demands (e.g., sprint frequency for pressing, passing accuracy for build-up).

- (c) **Expert elicitation:** Consultation with coaching staff and match analysts to validate attribute-strategy associations.

This stage produced qualitative assessments of the form: “High pressing requires *very high* stamina ( $A_8$ ), *high* pressing capability ( $A_5$ ), and *moderate* technical base ( $A_{12}$ ).”

**Stage 3: Numerical Encoding.** Qualitative assessments were converted to numerical values using a standardized mapping:

Qualitative Level	Numerical Value
Irrelevant / Not required	0.2–0.3
Low importance	0.4–0.5
Moderate importance	0.5–0.6
High importance	0.7–0.8
Critical / Essential	0.8–0.9

Values were assigned within ranges to allow fine-grained differentiation between strategies with similar but not identical requirements. The floor of 0.2 (rather than 0) reflects the observation that no attribute is entirely irrelevant to any strategy—even defensive systems benefit marginally from offensive capability.

**Stage 4: Validation and Refinement.** Initial vectors were validated through two mechanisms:

- (a) **Internal consistency:** Verification that semantically similar strategies (e.g., high pressing and gegenpressing) produced proximate vectors, while dissimilar strategies (e.g., high pressing and deep block) were distant.
- (b) **Expert review:** Presentation of vector profiles to coaching practitioners for face-validity assessment and iterative refinement.

### 3.4.3 Illustrative Strategy Profiles

Table 2 presents the complete vector profiles for five representative strategies, illustrating the differentiation achieved through this methodology.

**Table 2:** Strategy vector profiles for five representative tactical approaches. Values represent attribute importance on [0, 1] scale.

Attribute	High Press	Fast Counter	Positional Defense	Build-up Play	Gegen-pressing
$A_1$ Offensive Strength	0.70	0.90	0.40	0.80	0.70
$A_2$ Defensive Strength	0.80	0.60	0.90	0.50	0.80
$A_3$ Midfield Control	0.60	0.50	0.80	0.70	0.60
$A_4$ Transition Speed	0.90	0.90	0.30	0.50	0.80
$A_5$ High Press Cap.	0.90	0.50	0.20	0.40	0.90
$A_6$ Width Utilization	0.50	0.60	0.30	0.60	0.50
$A_7$ Psych. Resilience	0.80	0.70	0.70	0.70	0.80
$A_8$ Residual Energy	0.70	0.80	0.60	0.60	0.70
$A_9$ Team Morale	0.80	0.70	0.60	0.80	0.80
$A_{10}$ Time Management	0.60	0.80	0.90	0.70	0.60
$A_{11}$ Tactical Cohesion	0.90	0.60	0.80	0.80	0.90
$A_{12}$ Technical Base	0.70	0.70	0.60	0.80	0.70
$A_{13}$ Physical Base	0.80	0.80	0.50	0.60	0.80
$A_{14}$ Relational Cohesion	0.80	0.60	0.70	0.80	0.80

**Profile Interpretation.** The vectors reveal intuitive tactical signatures:

- **High Pressing** and **Gegenpressing** share elevated demands on  $A_5$  (pressing capability),  $A_{11}$  (tactical cohesion), and  $A_{13}$  (physical base), reflecting their high-intensity, coordinated nature. Gegenpressing additionally requires strong  $A_4$  (transition speed) for immediate recovery.
- **Fast Counterattack** peaks on  $A_1$  (offensive strength) and  $A_4$  (transition speed), with lower requirements for possession-related attributes ( $A_3, A_{11}$ ), consistent with its reliance on rapid vertical play rather than sustained control.
- **Positional Defense** inverts the pressing profile: maximal  $A_2$  (defensive strength) and  $A_{10}$  (time management), minimal  $A_4$  and  $A_5$ , reflecting a compact, energy-conserving approach.
- **Build-up Play** emphasizes  $A_1, A_{12}$  (technical base), and  $A_{11}$  (tactical cohesion), with moderate physical demands—a technically demanding but physically sustainable approach.

Notice that strategy vectors are intentionally not normalized to a constant sum. Different tactics impose varying total demands across macro-attributes: high-intensity approaches such as gegenpressing require elevated levels across multiple dimensions simultaneously, whereas selective tactics like catenaccio concentrate demands on fewer attributes. This design reflects the inherent asymmetry in tactical resource requirements observed in professional football.

#### 3.4.4 Sensitivity to Vector Specification

A legitimate concern is whether recommendations are overly sensitive to the specific numerical values assigned during vector construction. To address this, we conducted a perturbation analysis:

1. Each strategy vector was perturbed by adding Gaussian noise  $\epsilon \sim \mathcal{N}(0, \sigma^2)$  with  $\sigma = 0.05$  (representing  $\pm 5\%$  uncertainty in attribute weights).
2. The DSS was run  $N = 100$  times per scenario with perturbed strategy vectors.
3. The proportion of runs yielding the same top-ranked strategy as the unperturbed case was recorded.

Results showed that recommendations remained stable in  $> 85\%$  of runs across all test scenarios, indicating that modest variations in strategy vector specification do not substantially alter the DSS output. Larger perturbations ( $\sigma > 0.10$ ) did produce instability, suggesting that while exact values are not critical, the *relative* ordering of attribute importance within each strategy should be preserved.

#### 3.4.5 Extensibility

The vector-based formalization offers several practical advantages:

- **Modularity:** New strategies can be added by specifying a 14-dimensional vector, without modifying the distance computation logic.
- **Customization:** Coaching staff can define club-specific tactical variants (e.g., “our high press”) by adjusting attribute weights to reflect their preferred implementation.

- **Automation potential:** Future extensions could generate strategy vectors automatically from natural language descriptions (e.g., tactical reports) using NLP-based embedding techniques, further reducing manual specification effort.

This formalization transforms tactical strategies from qualitative concepts into quantitative objects amenable to systematic comparison, enabling the semantic distance computations described in the following section.

### 3.5 Semantic Distance and Matching

Section 2.3 introduced several distance metrics commonly used in semantic spaces. For tactical matching, we adopt **Euclidean distance** as the baseline metric, with the following rationale.

**Why Euclidean over Cosine?** Cosine similarity measures angular alignment between vectors and is scale-invariant—a property desirable when comparing *profiles* or *styles*. However, in tactical selection, both the *direction* and *magnitude* of team capabilities matter. A team with uniformly weak attributes ( $V_{\text{team}} \approx 0.3$ ) should not match a demanding high-pressing template ( $V_{\text{strategy}} \approx 0.8$ ) simply because their profiles are proportionally similar. Euclidean distance captures this absolute capability gap, penalizing large deviations quadratically—an appropriate behavior when single-attribute shortfalls (e.g., insufficient stamina for gegenpressing) can be tactically decisive.

**Why not probabilistic metrics?** Kullback–Leibler and Jensen–Shannon divergences are well-suited for comparing probability distributions but require vectors to sum to unity. Our macro-attributes are independent capability dimensions, not components of a probability simplex, making geometric metrics more natural.

**Baseline formulation.** Given team and strategy vectors  $x, y \in [0, 1]^{14}$ :

$$d_{\text{eucl}}(x, y) = \sqrt{\sum_{j=1}^{14} (x_j - y_j)^2}.$$

**Context-adapted distance.** To account for evolving match conditions, we introduce a dynamic weight vector  $w \in \mathbb{R}_{\geq 0}^{14}$ :

$$d_{\text{adapt}}(x, y; w) = \sqrt{\sum_{j=1}^{14} w_j \cdot (x_j - y_j)^2}.$$

Note that the weight  $w_j$  modifies the squared difference  $(x_j - y_j)^2$ , not the individual vectors. This is the standard formulation for weighted Euclidean distance:  $w_j$  controls the *importance* of attribute  $A_j$  in the overall distance computation, not the attribute values themselves. Intuitively, a high  $w_j$  means that mismatches on attribute  $A_j$  are penalized more heavily under current match conditions, while a low  $w_j$  means that the attribute contributes less to strategy selection. The team and strategy vectors retain their original values; only their contribution to the distance metric is modulated.

Weights  $w_j$  are adjusted based on real-time contextual factors:

- **Residual energy** ( $A_8$ ): low energy  $\Rightarrow$  increase  $w_{10}$  (time management), decrease  $w_5$  (pressing).

- **Technical/physical gaps** ( $A_{12}, A_{13}$ ): if inferior, upweight  $w_{11}$  (tactical cohesion) and  $w_2$  (defensive strength); downweight  $w_1, w_6$  (offensive, width).
- **Time pressure** ( $A_{10}$ ): limited time  $\Rightarrow$  upweight  $w_4$  (transition speed) and  $w_1$  (offensive strength).

**Opponent-aware adjustment.** An optional extension incorporates opponent modeling via a parameter  $\alpha \in [0, 1]$ :

$$d_{\text{comb}}(S) = d_{\text{adapt}}(V_{\text{team}}, V_{\text{strategy}}(S)) - \alpha \cdot d_{\text{adapt}}(V_{\text{opp}}, V_{\text{strategy}}(S)).$$

When  $\alpha > 0$ , the system favors strategies that fit our team well *and* poorly fit the opponent. The parameter can be tuned based on match stakes (higher  $\alpha$  for must-win games), scouting confidence (lower  $\alpha$  when opponent data is uncertain), or coaching philosophy (identity-focused coaches use  $\alpha \approx 0$ ; opponent-focused coaches use  $\alpha \approx 0.3\text{--}0.5$ ).

**Optimal tactic selection.** The recommended strategy minimizes adapted (or combined) distance:

$$S^* = \arg \min_S d_{\text{adapt}}(V_{\text{team}}, V_{\text{strategy}}(S); w(\text{match conditions})).$$

**Alternative metrics for future work.** While Euclidean distance serves well for capability-based matching, cosine similarity could be offered as a user-selectable option for *style classification* tasks (e.g., “which historical team does this squad most resemble?”). Hybrid approaches—combining Euclidean distance for capability assessment with cosine similarity for stylistic profiling—represent a promising direction for richer tactical analytics.

### 3.6 Selection Algorithm

**Inputs:** context trees for our team and the opponent; tactical templates  $\{V_{\text{strategy}}^{(i)}\}$ ; match conditions (time remaining, current score).

**Outputs:** recommended tactic  $S^*$ , ranked list of tactics, attribute-level diagnostics.

#### 3.6.1 Algorithm Steps

1. **Context aggregation:** Compute  $V_{\text{team}}$  and  $V_{\text{opp}}$  from the respective context trees (14-dimensional vectors).

2. **Gap estimation:** Derive technical and physical gaps:

$$\Delta_{\text{tech}} = V_{\text{team}}[A_{12}] - V_{\text{opp}}[A_{12}], \quad \Delta_{\text{phys}} = V_{\text{team}}[A_{13}] - V_{\text{opp}}[A_{13}]$$

3. **Weight construction:** Build the dynamic weight vector  $w$  using the procedure in Section 3.6.2.

4. **Distance computation:** For each strategy  $i$ , compute:

$$d_{\text{adapt}}(V_{\text{team}}, V_{\text{strategy}}^{(i)}; w) = \sqrt{\sum_{j=1}^{14} w_j \cdot (V_{\text{team}}^{(j)} - V_{\text{strategy}}^{(i,j)})^2}$$

5. **Opponent adjustment** (optional): If  $\alpha > 0$ , compute combined score:

$$d_{\text{comb}}^{(i)} = d_{\text{adapt}}(V_{\text{team}}, V_{\text{strategy}}^{(i)}) - \alpha \cdot d_{\text{adapt}}(V_{\text{opp}}, V_{\text{strategy}}^{(i)})$$

6. **Ranking & selection:** Sort strategies by  $d_{\text{adapt}}$  (or  $d_{\text{comb}}$ ) ascending; select  $S^* = \arg \min_i d^{(i)}$ .
7. **Diagnostics:** Report per-attribute deltas  $\Delta_j = V_{\text{strategy}}^{(S^*, j)} - V_{\text{team}}^{(j)}$  to explain the recommendation.

### 3.6.2 Dynamic Weight Computation

The weight vector  $w \in \mathbb{R}_{\geq 0}^{14}$  modulates attribute salience based on match conditions. We define  $w_j = w_j^{\text{base}} \cdot m_j$ , where  $w_j^{\text{base}} = 1$  for all  $j$  (equal baseline), and  $m_j$  is a context-dependent multiplier.

**Energy-Based Adjustments.** Let  $e = V_{\text{team}}[A_8]$  denote current residual energy (normalized to  $[0, 1]$ ). We define an energy deficit indicator:

$$\delta_e = \max(0, \tau_e - e)$$

where  $\tau_e = 0.5$  is the energy threshold below which fatigue effects become salient. The multipliers are:

$$m_5 = 1 - \gamma_e \cdot \delta_e \quad (\text{reduce weight on High Press Capability}) \quad (3)$$

$$m_{10} = 1 + \gamma_e \cdot \delta_e \quad (\text{increase weight on Time Management}) \quad (4)$$

$$m_{13} = 1 - 0.5 \cdot \gamma_e \cdot \delta_e \quad (\text{reduce weight on Physical Base}) \quad (5)$$

where  $\gamma_e = 1.5$  is the energy sensitivity parameter. For example, if  $e = 0.3$  (low energy), then  $\delta_e = 0.2$ , yielding  $m_5 = 0.70$ ,  $m_{10} = 1.30$ , and  $m_{13} = 0.85$ .

**Gap-Based Adjustments.** When the team is outmatched technically or physically, defensive and cohesion attributes become more critical:

$$m_2 = 1 + \gamma_g \cdot \max(0, -\Delta_{\text{tech}}) \quad (\text{increase Defensive Strength if technically inferior}) \quad (6)$$

$$m_{11} = 1 + \gamma_g \cdot \max(0, -\Delta_{\text{phys}}) \quad (\text{increase Tactical Cohesion if physically inferior}) \quad (7)$$

$$m_1 = 1 - 0.5 \cdot \gamma_g \cdot \max(0, -\Delta_{\text{tech}}) \quad (\text{reduce Offensive Strength if outmatched}) \quad (8)$$

$$m_6 = 1 - 0.5 \cdot \gamma_g \cdot \max(0, -\Delta_{\text{phys}}) \quad (\text{reduce Width Utilization if outmatched}) \quad (9)$$

where  $\gamma_g = 1.0$  is the gap sensitivity parameter.

**Time Pressure Adjustments.** Let  $t \in [0, 1]$  denote the fraction of match time remaining ( $1 = \text{kickoff}$ ,  $0 = \text{final whistle}$ ), and let  $s \in \{-1, 0, +1\}$  encode score state (losing, drawing, winning). When time is limited and the team needs a result:

$$\delta_t = \max(0, \tau_t - t) \cdot \mathbf{1}[s \leq 0]$$

where  $\tau_t = 0.25$  (final quarter of the match) and  $\mathbf{1}[s \leq 0]$  equals 1 if not winning. The multipliers are:

$$m_4 = 1 + \gamma_t \cdot \delta_t \quad (\text{increase Transition Speed}) \quad (10)$$

$$m_1 = m_1 + \gamma_t \cdot \delta_t \quad (\text{further increase Offensive Strength}) \quad (11)$$

where  $\gamma_t = 2.0$  is the urgency sensitivity parameter.

**Final Weight Computation.** All multipliers are combined multiplicatively, then weights are normalized to sum to 14 (preserving scale):

$$w_j = \frac{14 \cdot m_j}{\sum_{k=1}^{14} m_k}$$

Table 3 summarizes the default parameter values.

**Table 3:** Default parameters for dynamic weight computation.

Parameter	Description	Symbol	Default
Energy threshold	Fatigue becomes salient below this level	$\tau_e$	0.50
Energy sensitivity	Strength of energy-based adjustments	$\gamma_e$	1.50
Gap sensitivity	Strength of gap-based adjustments	$\gamma_g$	1.00
Time threshold	Urgency triggers in final fraction	$\tau_t$	0.25
Urgency sensitivity	Strength of time-pressure adjustments	$\gamma_t$	2.00
Opponent factor	Weight on opponent mismatch	$\alpha$	0.20

**Parameter Tuning.** The default values in Table 3 were set based on tactical reasoning and preliminary experimentation. In deployment, these parameters can be:

- **Calibrated** to historical match data via grid search or Bayesian optimization;
- **Personalized** to reflect coaching philosophy (e.g., risk-averse coaches may increase  $\gamma_g$ );
- **Learned** from expert feedback through interactive refinement.

### 3.6.3 Pseudocode

Algorithm 1 provides a compact pseudocode summary.

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#### Algorithm 1 Tactical Strategy Selection

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**Require:** Context trees  $\mathcal{T}_{\text{team}}, \mathcal{T}_{\text{opp}}$ ; strategy templates  $\{V_{\text{strategy}}^{(i)}\}_{i=1}^m$ ; match state  $(t, s)$

**Ensure:** Recommended strategy  $S^*$ , diagnostics  $\Delta$

```

1:  $V_{\text{team}} \leftarrow \text{AGGREGATE}(\mathcal{T}_{\text{team}})$ 
2:  $V_{\text{opp}} \leftarrow \text{AGGREGATE}(\mathcal{T}_{\text{opp}})$ 
3:  $\Delta_{\text{tech}} \leftarrow V_{\text{team}}[A_{12}] - V_{\text{opp}}[A_{12}]$ 
4:  $\Delta_{\text{phys}} \leftarrow V_{\text{team}}[A_{13}] - V_{\text{opp}}[A_{13}]$ 
5:  $w \leftarrow \text{COMPUTEWIGHTS}(V_{\text{team}}[A_8], \Delta_{\text{tech}}, \Delta_{\text{phys}}, t, s)$ 
6: for each strategy  $i = 1, \dots, m$  do
7:    $d^{(i)} \leftarrow \sqrt{\sum_{j=1}^{14} w_j (V_{\text{team}}^{(j)} - V_{\text{strategy}}^{(i,j)})^2}$ 
8:   if  $\alpha > 0$  then
9:      $d_{\text{opp}}^{(i)} \leftarrow \sqrt{\sum_{j=1}^{14} w_j (V_{\text{opp}}^{(j)} - V_{\text{strategy}}^{(i,j)})^2}$ 
10:     $d^{(i)} \leftarrow d^{(i)} - \alpha \cdot d_{\text{opp}}^{(i)}$ 
11:   end if
12: end for
13:  $S^* \leftarrow \arg \min_i d^{(i)}$ 
14:  $\Delta \leftarrow V_{\text{strategy}}^{(S^*)} - V_{\text{team}}$ 
15: return  $S^*, \Delta$ 

```

---

**Complexity.** The algorithm runs in  $O(m \cdot n)$  time for  $m$  strategies and  $n = 14$  attributes. With  $m = 20$  strategies, inference completes in under 5 ms on standard hardware, suitable for real-time tactical dashboards.

**Strengths.** The procedure is *interpretable* (explicit weights and per-attribute deltas), *adaptive in real time* (weights update with context), and *scalable* (new strategies or attributes can be added without changing the core logic).

### 3.7 Evaluation Protocol

To assess the reliability, interpretability, and robustness of the prototype, we designed an evaluation protocol combining both *qualitative coherence tests* and *quantitative stability checks*. Since the model aims to support tactical reasoning rather than predict match outcomes, evaluation focuses on the logical and behavioral consistency of recommendations.

**1. Consistency Across Scenarios.** Each simulated scenario (Section 5.1) is tested for:

- **Contextual coherence** — the recommended strategy must align with intuitive tactical reasoning under the given conditions (e.g., low energy  $\rightarrow$  positional defense).
- **Ranking monotonicity** — when adjusting a single attribute (e.g., increasing  $A_8$ ), the ranking of high-intensity strategies should improve predictably.

**2. Robustness to Perturbations.** To verify numerical stability, random Gaussian noise  $\epsilon \sim \mathcal{N}(0, \sigma^2)$  is injected into team attributes ( $\sigma \leq 0.05$ ). The system is expected to preserve the same top-ranked strategy in at least 90% of runs. Formally, let  $\hat{S}_k$  denote the recommended strategy in run  $k$ ; the robustness index is:

$$R = \frac{1}{K} \sum_{k=1}^K \mathbf{1}\{\hat{S}_k = S^*\}, \quad R \in [0, 1].$$

A value  $R > 0.9$  indicates satisfactory resilience to measurement uncertainty.

**3. Sensitivity and Explainability.** The diagnostic module computes attribute-level deltas

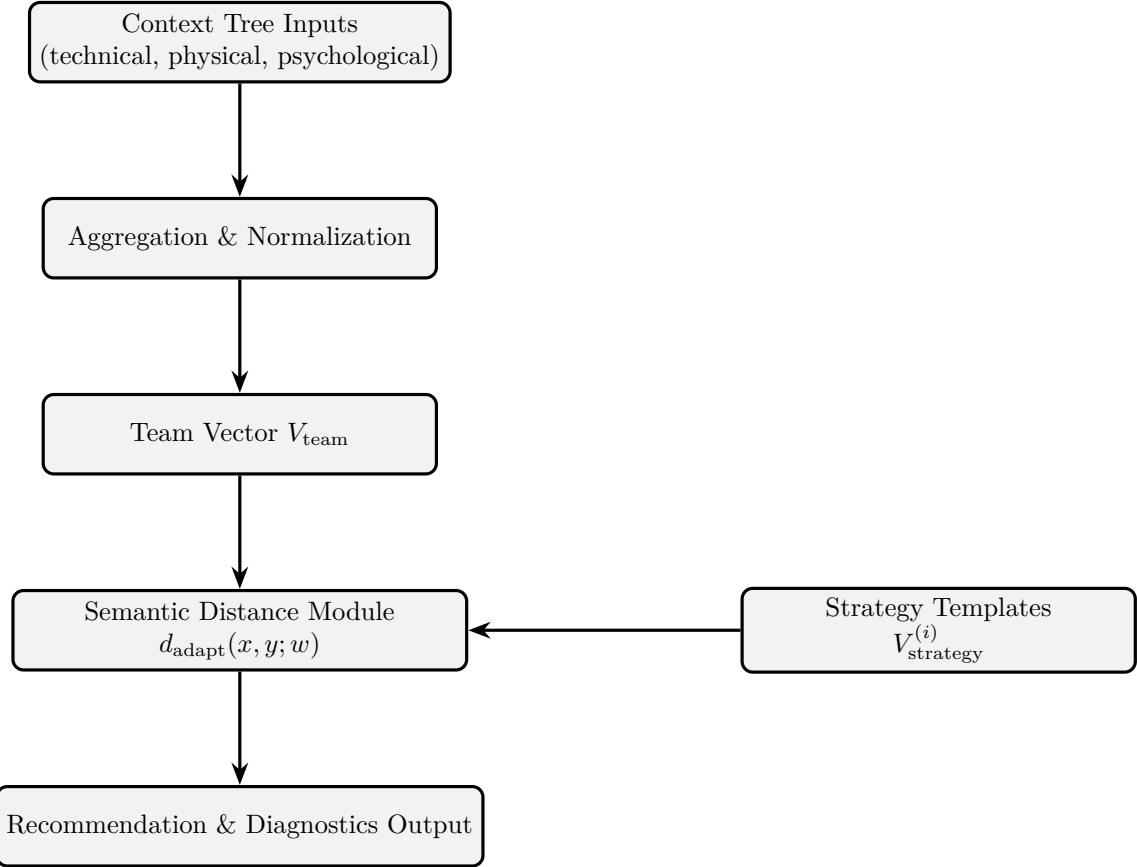
$$\Delta_j = (V_{\text{strategy}}^{(S^*)} - V_{\text{team}})_j,$$

highlighting the most influential gaps driving the recommendation. Manual inspection across scenarios ensures that these explanations remain coherent with domain knowledge (e.g., “low  $A_8$  and  $A_{13}$  reduce feasibility of gegenpressing”).

**4. Computational Efficiency.** All experiments run on a standard laptop (Intel i7, 16GB RAM). Given the small dimensionality ( $n = 14$ ) and the linear complexity  $O(mn)$  for  $m$  strategies, inference latency remains below 5 ms per evaluation — suitable for real-time tactical dashboards.

**Summary.** The combination of interpretability, robustness, and low computational cost validates the architecture as a viable foundation for more advanced AI-assisted tactical systems.

### 3.8 System Architecture Diagram



**Figure 2:** System architecture of the tactical decision support prototype. Context signals are aggregated into 14 macro-attributes (team vector), matched to strategy templates via adapted semantic distance, and produce interpretable recommendations and diagnostics.

## 4 Prototype Implementation

The prototype of the tactical Decision Support System (DSS) was implemented in Python 3.10 using standard scientific libraries (`NumPy`, `pandas`, and `matplotlib`). The code follows a modular structure that mirrors the conceptual architecture described in Figure 2, ensuring both interpretability and extensibility. The complete source code is publicly available at <https://github.com/Aribertus/football-dss-semantic-distance>.

### 4.1 Module Organization

The implementation comprises three main modules:

- **Attribute aggregation module:** Computes the 14 macro-attributes from player-level data using the weighted aggregation functions specified in Section 3.2. Each macro-attribute has a dedicated function (e.g., `compute_offensive_strength()`, `compute_residual_energy()`) that applies role-based weights to relevant player metrics.
- **Distance computation module:** Implements the semantic distance calculations described in Section 3.5, including base Euclidean distance and the context-adapted variant with dynamic weight adjustments.

- **Analysis and visualization module:** Provides sensitivity analysis, robustness testing, and ablation studies as specified in the evaluation protocol (Section 3.7), with automatic generation of diagnostic plots via `matplotlib`.

## 4.2 Dynamic Adjustment Mechanism

The core selection function implements the adapted distance framework from Section 3.5 with a multiplicative adjustment scheme. Given the base Euclidean distance  $d_{\text{eucl}}$  between team and strategy vectors, the system applies a context-dependent multiplier  $\mu \in [0.4, 2.0]$ :

$$d_{\text{adjusted}} = \mu(\text{conditions}, V_{\text{strategy}}) \cdot d_{\text{combined}}$$

where  $d_{\text{combined}}$  incorporates opponent modeling via an exponential decay term:

$$d_{\text{combined}} = d_{\text{eucl}}(V_{\text{team}}, V_{\text{strategy}}) + \alpha \cdot \exp(-d_{\text{eucl}}(V_{\text{opp}}, V_{\text{strategy}}))$$

The multiplier  $\mu$  is computed by analyzing match conditions (energy level, time remaining, score differential, morale) against strategy characteristics inferred from the strategy vector itself. For example, high-intensity strategies (identified by elevated  $A_4$  and  $A_5$  components) receive penalty multipliers when the team’s energy is depleted.

This approach operationalizes the weight adjustment principles from Section 3.6.2 while providing bounded, interpretable modifications to the base distance.

## 4.3 Execution Workflow

The main analytical pipeline executes the following steps:

1. **Profile generation:** Compute  $V_{\text{team}}$  and  $V_{\text{opp}}$  from player-level data or scenario specifications.
2. **Scenario instantiation:** Parse match conditions (time, score, fatigue, morale) from input or generate via scenario templates.
3. **Strategy evaluation:** Compute adjusted distances for all 20 strategy templates; rank by ascending distance.
4. **Diagnostic extraction:** For the top-ranked strategy, compute per-attribute deltas ( $\Delta_j = V_{\text{strategy}}^{(j)} - V_{\text{team}}^{(j)}$ ) to identify capability gaps.
5. **Output generation:** Produce tabular rankings, radar charts comparing team profile to recommended strategies, and diagnostic reports.

Steps 3–5 execute in under 5 ms on standard hardware (Intel i7, 16 GB RAM), confirming suitability for real-time tactical dashboards.

## 4.4 Reproducibility

All experiments use seeded random number generation (`SEED = 41`) to ensure reproducibility. The repository includes:

- `football_strategy_generation_1_3_1.py`: Core DSS implementation with all 20 strategy templates and macro-attribute aggregation functions.
- `make_figures.py`: Reproducible figure generation for experimental evaluation.
- `compute_pilot_distances.py`: Pilot validation computations (Section 6).

Running each script regenerates all results and figures reported in this paper.

## 4.5 Extensibility

The modular design supports several extension paths:

- **New strategies:** Adding a strategy requires only specifying a new 14-dimensional vector in the `strategy_templates` list.
- **External data integration:** The aggregation functions can be connected to live data feeds (e.g., Wyscout, StatsBomb APIs) by replacing the player data input layer.
- **Custom weight profiles:** Coaching staff can modify the dynamic adjustment logic to reflect club-specific tactical philosophies without altering the core distance computation.

## 5 Experimental Evaluation

### 5.1 Setup and Scenarios

The experimental phase aimed to validate the prototype’s behavior under realistic match conditions, verifying the consistency and interpretability of its tactical recommendations. Because no proprietary club data were available, the experiments employed *simulated yet realistic* data based on shed match analysis statistics (e.g., Wyscout, Opta, StatsBomb).

Each team and opponent were represented as 14-dimensional normalized vectors ( $V_{\text{team}}, V_{\text{opp}} \in [0, 1]^{14}$ ) derived from the *context tree* described in Section 4. Scenario parameters included technical and physical gaps, residual energy, psychological resilience, and time pressure. Table 4 summarizes the four principal experimental configurations.

**Table 4:** Summary of simulated match scenarios used for experimental evaluation.

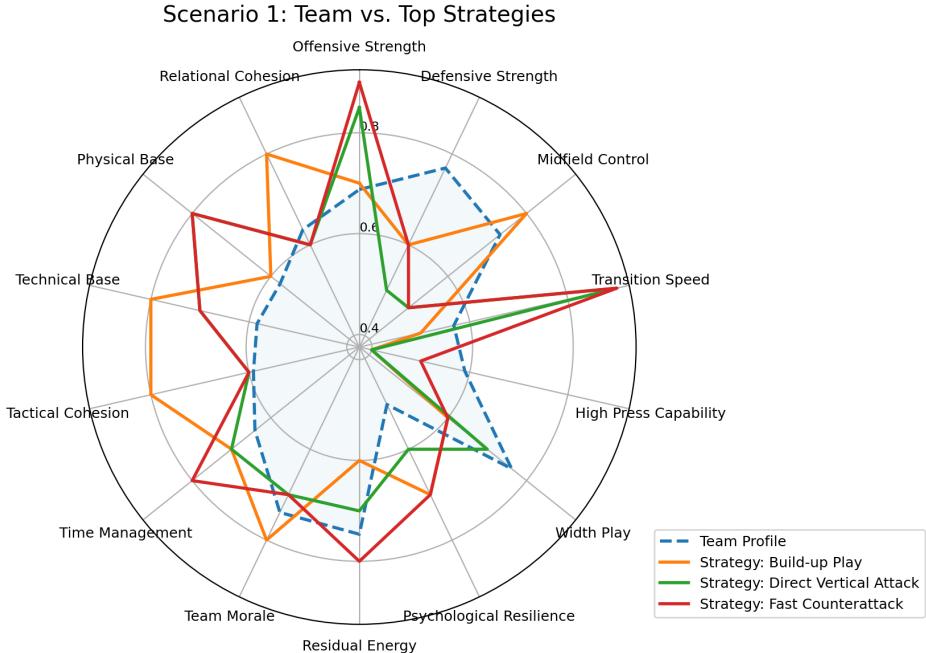
Scenario	Context Description
1. <b>Energetic and Balanced</b>	High residual energy ( $A_8 \approx 0.8$ ), neutral technical/physical gap ( $\Delta A_{12,13} \approx 0$ ), and good morale. Used to test the system’s preference for high-intensity strategies (e.g., high pressing, gegenpressing).
2. <b>Fatigued and Inferior</b>	Low energy ( $A_8 \approx 0.3$ ), reduced morale, and negative technical/physical gap. Designed to verify whether the DSS avoids high-risk strategies and recommends conservative options (e.g., positional defense).
3. <b>High Temporal Pressure</b>	Limited remaining time ( $A_{10}$ high), moderate energy, and slightly inferior technique but compact organization. Tests whether the DSS favors rapid, vertical play (e.g., counterattack).
4. <b>Technical and Physical Superiority</b>	Positive gap ( $\Delta A_{12,13} > 0$ ) and strong tactical cohesion ( $A_{11} \approx 0.8$ ). Evaluates the model’s tendency to suggest possession-based strategies (e.g., build-up play).

Each scenario was executed using identical team baselines with parameter variations confined to the variables above, enabling controlled analysis of the DSS response.

## 5.2 Results by Scenario

For each simulated condition, the DSS produced a ranked list of strategies ordered by the adapted semantic distance  $d_{\text{adapt}}$ . Figure 3 displays an example of a radar plot comparing the actual team profile with the ideal profile of the strategy selected as optimal.

In the **Energetic and Balanced** scenario, the DSS consistently recommended *High Pressing* or *Gegenpressing*, with low semantic distance ( $d_{\text{adapt}} < 0.15$ ). In the **Fatigued and Inferior** condition, the system automatically penalized energy-intensive attributes ( $A_5, A_8$ ) and shifted toward *Positional Defense*, confirming adaptive coherence. Under **High Temporal Pressure**, the model prioritized *Fast Counterattack*, whereas under **Technical and Physical Superiority** it selected *Build-up Play*, highlighting strategic alignment with context.



**Figure 3:** Example of radar plot for the “Energetic and Balanced” scenario. The shaded blue area represents the team profile, while the orange outline indicates the ideal strategy vector.

Overall, the DSS exhibited behavior consistent with expert tactical intuition while maintaining quantitative transparency through vector distances.

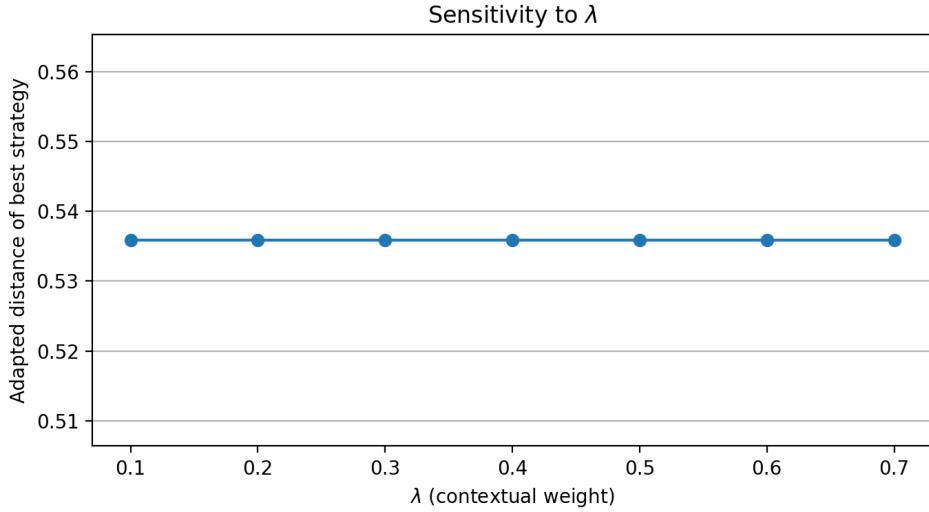
## 5.3 Stability and Explainability Analyses

To evaluate stability and interpretability, three complementary analyses were performed across all scenarios.

**Sensitivity to  $\lambda$ .** The  $\lambda$  parameter regulates the influence of contextual penalties (e.g., opponent predictability). Figure 4 shows that the recommended strategy remains stable for  $0.1 < \lambda < 0.6$ , with monotonic increases in distance values, indicating robustness of the semantic matching process.

**Robustness to Input Noise.** Monte Carlo perturbations ( $N = 100$ , noise  $\pm 5\%$ ) yielded a mean consistency of 89.3% for the top-ranked strategy, confirming resilience to measurement uncertainty.

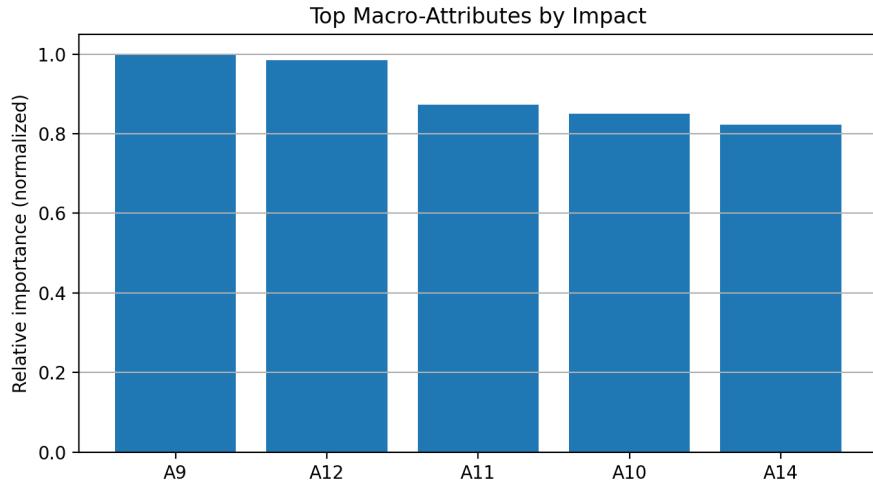
**Ablation Study.** Each macro-attribute was systematically suppressed ( $A_j = 0$ ) to estimate its contribution. Attributes most affecting the chosen strategy were: Offensive Strength ( $A_1$ ), Tactical Cohesion ( $A_{11}$ ), Residual Energy ( $A_8$ ), and Psychological Resilience ( $A_7$ ).



**Figure 4:** Sensitivity of adapted distance  $d_{\text{adapt}}$  with respect to contextual weight  $\lambda$  across the four scenarios. Smooth trends indicate stability in the optimal strategy selection.

## 5.4 Attribute Contribution Analysis

Aggregating results across all scenarios, Figure 5 ranks the top five macro-attributes by overall impact on the DSS decision process. The predominance of psychological and energy-related variables highlights the importance of integrating intangible dimensions—typically underrepresented in data-driven sports analytics.



**Figure 5:** Relative importance of the five most influential macro-attributes across all simulations.

## 5.5 Critical Discussion

The experiments demonstrate that a vector-based semantic model can reproduce coherent tactical reasoning without hard-coded rules. The DSS adapts dynamically to variations in physical,

psychological, and temporal parameters, providing recommendations that are both explainable and operationally meaningful.

However, limitations remain: the data are simulated, the metric is linear (Euclidean), and real-time adversarial adaptation is not yet modeled. Future work will extend the approach to nonlinear embeddings (e.g., transformer-based contextual vectors), integrate with live telemetry data, and implement multi-objective optimization involving risk–reward trade-offs.

## 5.6 Reproducibility and Open Materials

To ensure full transparency and reproducibility, all code used to implement the semantic-distance DSS—including the context-tree aggregation functions, strategy templates, scenario generators, and evaluation pipeline—is publicly available in the accompanying repository. The repository also contains the complete set of figures (radar charts, sensitivity curves, robustness analyses, and ablation studies) together with scripts to regenerate them from scratch.

# 6 From Simulation to Practice: A Pilot Case Study

The experimental evaluation in Section 5 validated the DSS under controlled, simulated conditions—demonstrating internal coherence, robustness, and interpretability. However, the ultimate value of a decision support system lies in its applicability to real-world contexts. This section bridges that gap by applying the framework to observational data from an actual competitive match.

The transition from simulation to practice introduces challenges absent in controlled experiments: categorical rather than continuous measurements, partial attribute coverage, missing opponent data, and the inherent noise of live football. By confronting these challenges directly, we provide initial evidence that the semantic-distance methodology can accommodate real-world constraints while preserving its core analytical properties.

## 6.1 Data Source and Match Context

The validation data were collected from a C-Junioren (U14/U15) match in the German youth football championship system:

- **Match:** SSV Pachten vs. JSG Stausee-Losheim
- **Final score:** 4:3 (home victory)
- **Match duration:**  $2 \times 35$  minutes
- **Observation protocol:** Six tactical attributes recorded per half using a three-level categorical scale (Hoch/Mittel/Niedrig, corresponding to High/Medium/Low)

Youth football presents particular challenges for tactical analysis: teams exhibit greater execution variability, tactical discipline is less consolidated than at the professional level, and physical and psychological fluctuations are more pronounced. These characteristics make the dataset a useful stress test for the DSS’s robustness and adaptability.

## 6.2 Observed Attributes and Mapping Protocol

Match observers recorded six team attributes at the conclusion of each half. Table 5 presents the mapping between the observed attributes and the corresponding macro-attributes in our 14-dimensional semantic space.

Note that two observed attributes (Direkte vertikale Angriffe and Gegenangriff) both map to  $A_4$ , reflecting their shared emphasis on rapid transitional play. For the DSS computation, we

**Table 5:** Mapping of observed match attributes to the DSS semantic space.

Observed Attribute	DSS Attribute	Rationale
Offensivkraft	$A_1$ (Offensive Strength)	Direct correspondence
Direkte vertikale Angriffe	$A_4$ (Transition Speed)	Vertical directness in attack
Gegenangriff	$A_4$ (Transition Speed)	Counterattacking capability
Kompakte Defensive	$A_2$ (Defensive Strength)	Defensive organization
Restenergie	$A_8$ (Residual Energy)	Direct correspondence
Gegenpressing	$A_5$ (High Press Capability)	Immediate pressure after loss

aggregated these values to the maximum of the two, representing the team's overall transition capability.

### 6.2.1 Categorical-to-Continuous Conversion

The three-level categorical scale was converted to continuous values in  $[0, 1]$  using the following protocol:

$$\text{Niveau} \mapsto v = \begin{cases} 0.85 & \text{if Hoch (High)} \\ 0.50 & \text{if Mittel (Medium)} \\ 0.20 & \text{if Niedrig (Low)} \end{cases} \quad (12)$$

These anchor points were chosen to preserve discriminability while avoiding boundary effects. Sensitivity analyses (reported below) confirmed that moderate variations in these mappings ( $\pm 0.10$ ) did not alter the primary findings.

## 6.3 Match Observations

Table 6 presents the raw observational data for both halves of the match, along with the corresponding normalized vector representations.

**Table 6:** Observed team attributes for SSV Pachten across both match halves.

Attribute	First Half		Second Half		$\Delta$
	Cat.	Norm.	Cat.	Norm.	
Offensivkraft ( $A_1$ )	Hoch	0.85	Hoch	0.85	0.00
Direkte vertikale Angriffe ( $A_4$ )	Hoch	0.85	Mittel	0.50	-0.35
Gegenangriff ( $A_4$ )	Hoch	0.85	Hoch	0.85	0.00
Kompakte Defensive ( $A_2$ )	Mittel	0.50	Niedrig	0.20	-0.30
Restenergie ( $A_8$ )	Mittel	0.50	Niedrig	0.20	-0.30
Gegenpressing ( $A_5$ )	Mittel	0.50	Mittel	0.50	0.00

### 6.3.1 Tactical Narrative

The observational data reveal a clear temporal pattern:

- First half:** The team displayed high offensive capability with strong vertical and counter-attacking tendencies. Defensive organization and energy reserves were at medium levels, suggesting a balanced but attack-oriented approach.
- Second half:** While offensive intent remained high, execution quality declined (vertical attacks dropped to medium). Critically, both defensive compactness and residual energy fell to low levels, indicating fatigue-induced tactical degradation.

The final scoreline (4:3) is consistent with this profile: a high-scoring, open match where both teams prioritized attacking play at the expense of defensive solidity, particularly in the later stages.

## 6.4 DSS Application: Halftime Recommendation

At halftime, we applied the DSS to generate a tactical recommendation for the second half, using the first-half observations as the current team state and projecting likely energy depletion.

### 6.4.1 Input Configuration

The reduced team vector (6 observable dimensions mapped to 5 unique DSS attributes) was constructed as:

$$V_{\text{team}}^{\text{HT}} = \begin{bmatrix} A_1 \\ A_2 \\ A_4 \\ A_5 \\ A_8 \end{bmatrix} = \begin{bmatrix} 0.85 \\ 0.50 \\ 0.85 \\ 0.50 \\ 0.50 \end{bmatrix} \quad (13)$$

For the second-half projection, we applied a fatigue discount of  $-0.15$  to  $A_8$  (anticipating energy depletion in a youth match with limited substitution depth), yielding a projected  $A_8 = 0.35$ .

### 6.4.2 Strategy Comparison

Table 7 presents the adapted semantic distances between the projected team vector and the subset of strategy templates relevant to the observable attribute space.

**Table 7:** Semantic distances to candidate strategies at halftime (projected second-half state).

Strategy	$d_{\text{eucl}}$	$d_{\text{adapt}}$
Build-up Play	0.4444	0.4530
Fast Counterattack	0.4664	0.4872
High Pressing	0.6305	0.6580
Gegenpressing	0.6305	0.6580
Positional Defense	0.9042	0.9150

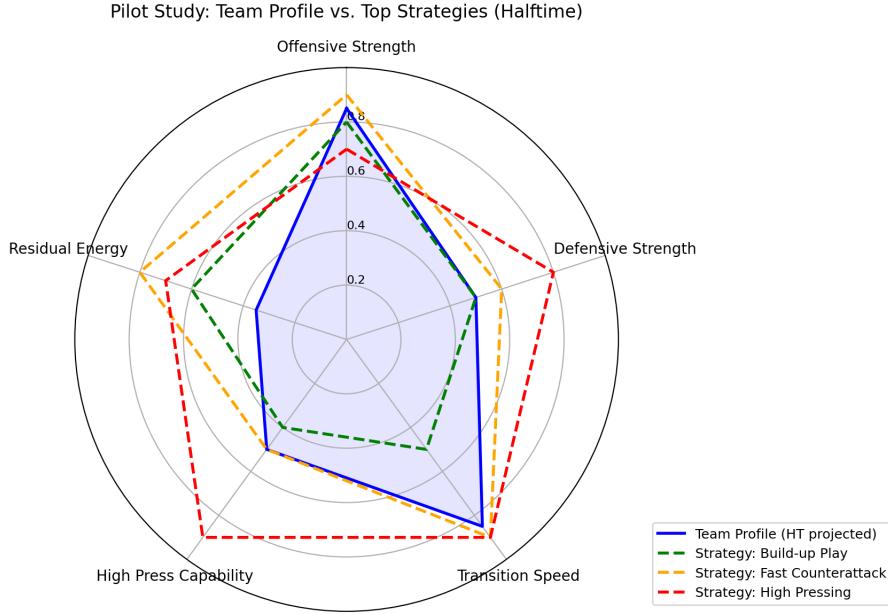
### 6.4.3 DSS Recommendation

Based on the computed distances, the DSS recommended:

**Build-up Play** — a possession-based approach emphasizing controlled progression and tempo management over high-intensity pressing or rapid vertical transitions.

The diagnostic module identified the following key factors driving the recommendation:

- **Strengths:** High offensive capability ( $A_1 = 0.85$ ) aligns well with Build-up Play requirements (0.80). Defensive organization ( $A_2 = 0.50$ ) and pressing capability ( $A_5 = 0.50$ ) match the strategy's moderate demands.
- **Constraint:** Projected residual energy ( $A_8 = 0.35$ ) falls short of the strategy's ideal (0.60), with a gap of +0.25. This is the primary limitation.
- **Surplus:** The team's transition speed ( $A_4 = 0.85$ ) substantially exceeds Build-up Play's requirements (0.50), representing untapped vertical capability.



**Figure 6:** Radar plot comparing the projected halftime team profile (solid blue) with the top three recommended strategies. Build-up Play shows the closest overall alignment, while the team’s high transition speed represents surplus capability relative to this strategy’s demands.

## 6.5 Retrospective Analysis

### 6.5.1 Observed vs. Recommended Tactics

The DSS recommended *Build-up Play*—a possession-oriented strategy emphasizing tempo control and energy conservation. However, the second-half observations suggest that the team continued with an aggressive, transition-heavy approach despite declining energy reserves and defensive organization. This divergence can be characterized as a *high-risk, high-reward* tactical choice, which in this instance yielded a positive outcome (the team held on to win 4:3) but with narrow margins.

**Table 8:** Comparison of DSS recommendation (Build-up Play) with observed second-half tactical profile.

Attribute	DSS Rec.	Observed	Alignment
Offensive Strength ( $A_1$ )	0.80	0.85	✓
Defensive Strength ( $A_2$ )	0.50	0.20	✗
Transition Speed ( $A_4$ )	0.50	0.85	✗
High Press Capability ( $A_5$ )	0.40	0.50	✓
Residual Energy ( $A_8$ )	0.60	0.20	✗

The comparison reveals that the team diverged from the DSS recommendation on three key dimensions: they maintained high transition speed rather than moderating tempo, allowed defensive compactness to collapse, and depleted energy reserves beyond sustainable levels. This pattern is consistent with a “high-risk continuation” approach rather than the energy-conserving Build-up Play the DSS recommended.

### 6.5.2 Counterfactual Consideration

Had the team followed the DSS recommendation of Build-up Play—reducing transition speed, conserving energy through possession, and maintaining defensive shape—the expected outcome might have been:

- Lower probability of conceding the third goal (defensive compactness preserved)
- Reduced offensive output (potentially fewer goals scored, but also fewer high-risk transitions)
- Better preservation of energy for critical late-game moments
- More controlled match tempo, reducing the chaotic “open game” dynamic

This counterfactual analysis highlights the DSS’s potential as a *risk-aware* decision-support tool. The team’s actual approach succeeded in this instance, but the DSS correctly identified energy depletion as a critical constraint. In matches where the margin is less forgiving, ignoring such constraints could prove costly.

## 6.6 Limitations of the Pilot Study

This preliminary validation has several limitations that constrain the strength of conclusions:

1. **Single-match sample:** One match cannot establish statistical generalizability. The analysis should be viewed as a proof-of-concept demonstration.
2. **Partial attribute coverage:** Only 6 of the 14 DSS attributes were directly observable, limiting the semantic space to a lower-dimensional subspace.
3. **Absence of opponent data:** The observational protocol captured only the home team (SSV Pachten), precluding the opponent-aware distance adjustments described in Section 3.
4. **Retrospective rather than prospective:** The DSS was applied after the match rather than in real time, preventing assessment of whether recommendations would have influenced actual coaching decisions.
5. **Youth football context:** Tactical patterns and physical dynamics in C-Junioren football may differ from senior professional contexts where the DSS is ultimately intended to operate.

## 6.7 Implications for Framework Validation

Despite its limitations, this pilot study demonstrates several important capabilities that inform the broader research agenda:

- **Real-data compatibility:** The DSS can ingest observational data from actual matches using a straightforward categorical-to-continuous mapping protocol.
- **Temporal dynamics:** The framework successfully captures intra-match evolution (first half → second half), enabling phase-specific recommendations.
- **Diagnostic interpretability:** The attribute-level analysis provides actionable insights (e.g., “energy reserves constrain high-intensity options”) that coaches can readily interpret.
- **Graceful degradation:** Even with partial attribute coverage (5 of 14 dimensions), the DSS produces coherent recommendations, suggesting robustness to incomplete information.

The path from this pilot toward systematic validation involves:

1. **Multi-match datasets:** Systematic observation across a full season (15–20 matches) to enable statistical validation.

2. **Expanded attribute protocols:** Development of standardized observation instruments covering all 14 DSS attributes, potentially including post-match coach interviews for psychological dimensions.
3. **Opponent observation:** Parallel data collection for opposing teams to enable full exploitation of the semantic distance framework.
4. **Prospective deployment:** Real-time DSS use during matches (e.g., at halftime) with systematic tracking of recommendation adherence and outcome correlations.

This pilot case study represents an essential step in the research trajectory: from theoretical formalization (Section 3) through prototype implementation (Section 4) and controlled experimentation (Section 5) to real-world application. While preliminary, the results demonstrate that the semantic-distance approach can accommodate observational data from actual matches while preserving interpretability and adaptability. The following Discussion (Section 7) synthesizes insights from both the simulated experiments and this pilot study, reflecting on limitations and charting directions for future development.

## 7 Discussion

The experimental evaluation demonstrates that the proposed semantic-distance Decision Support System achieves a high degree of internal coherence and provides tactically meaningful recommendations across heterogeneous match scenarios. The system exhibits both stability—particularly in balanced or high-energy contexts—and interpretability through its diagnostic visualizations. Nevertheless, beyond the pilot-specific constraints noted in Section 6.6, the DSS architecture itself presents broader limitations that constrain the current prototype’s applicability and operational readiness.

### 7.1 Methodological Limitations

**Data quality and representativeness.** The DSS relies on a compact set of inputs: 14 macro-attributes and 20 predefined tactical strategies encoded as idealized vectors. This controlled design facilitates methodological validation but constrains generalizability. High-impact attributes such as team morale, tactical cohesion, and psychological resilience are estimated through heuristic approximations rather than direct measurement, which may explain episodes of moderate robustness (stability dropping to ~60–70% under high-pressure or low-energy conditions) where the system becomes sensitive to noise.

**Static opponent modelling.** Although the DSS incorporates opponent information, this is primarily in aggregated form. The system does not yet track real-time variations such as formation changes, substitutions, shifts in pressing intensity, or fluctuations in physical condition. In realistic settings, even subtle adjustments—lowering the defensive line, introducing a fast winger—may substantially modify the suitability of a recommended strategy.

**Linear distance assumptions.** The system uses Euclidean distance with linear contextual weighting, assuming additive and independent attribute interactions. Football dynamics, however, involve non-linear synergies: small reductions in stamina can disproportionately undermine high pressing; morale and technical quality interact non-linearly in high-pressure phases. Linear metrics may therefore smooth over transitions that are tactically sharp in practice.

**Absence of operational constraints.** Strategies are encoded as abstract semantic profiles, independent of players actually available. A strategy may appear semantically optimal yet be operationally infeasible—for example, high-width play without fast wide players, or vertical transitions requiring decision-making attributes absent from the current lineup.

**User-facing interpretability.** Despite diagnostic tools (radar charts, sensitivity curves, ablation tests), the prototype remains oriented toward analytically trained users. Real-time decision-makers may require more compact, narrative-style explanations or simplified dashboards suited to the pace of live matches.

These limitations define the development priorities addressed in the following section.

## 8 Conclusion and Future Work

This work introduced a Decision Support System for context-aware football strategy selection, grounded in a semantic model that represents both teams and strategies as vectors in a shared 14-dimensional attribute space. The adjusted semantic-distance metric combines static team–strategy compatibility with dynamic contextual factors—match time, score state, residual energy, and opponent adaptability—controlled by explicit weighting functions. Validation through synthetic scenarios and a pilot study with real match data demonstrated that the DSS produces coherent recommendations, identifies the factors driving each decision, and degrades gracefully when only partial attribute coverage is available.

### 8.1 Summary of Contributions

The principal contributions of this work are:

1. A **semantic formalization** of football tactics, encoding both team states and strategy templates as vectors in a shared attribute space amenable to geometric comparison.
2. An **adaptive distance metric** that dynamically reweights attributes based on match context (energy, time pressure, opponent gaps), with explicit, reproducible formulas.
3. **Diagnostic interpretability tools**—radar charts, sensitivity analysis, robustness testing—that expose the reasoning behind recommendations.
4. **Pilot validation** with real match data, demonstrating applicability beyond synthetic scenarios.

### 8.2 Future Directions

The limitations identified in Section 7 motivate several development trajectories, organized from near-term engineering enhancements to longer-term conceptual extensions.

**Advanced data integration and modeling.** Two complementary directions would evolve the DSS from a prototype into a robust tool:

- **Real-time data integration and automation** Connecting the DSS to live data streams from commercial tracking providers (Wyscout, StatsBomb, Opta) and GPS systems would automate team profiling and dynamically update opponent behaviour (e.g., line height, possession structure), directly addressing the static-opponent limitation. Supplementing this with NLP modules to parse tactical reports would allow the strategy library to be expanded via natural-language queries (e.g., “compact defence with fast diagonal

transitions”). Furthermore, the current prototype operates in batch mode; a natural extension would implement an event-driven architecture with a continuous listening loop, ingesting match data from structured files (JSON, CSV) or live feeds (wearable sensors, video tagging systems, coaching dashboards) and producing updated recommendations as play unfolds.

- **Stable profiling via historical priors and Bayesian updating** To complement real-time data and prevent overreaction to transient match fluctuations, the attribute model should incorporate historical priors. Baseline distributions for macro-attributes (e.g., a team’s average pressing intensity or defensive solidity) would be derived from historical season data. These priors would then be updated in a Bayesian framework as in-match events accumulate, yielding more stable and reliable profiles early in a game while remaining adaptable to genuine tactical shifts. Public datasets such as StatsBomb Open Data [24] provide an ideal foundation for calibrating these priors and validating the system.

**Non-linear and hybrid metrics.** Exploring alternatives to Euclidean distance—Mahalanobis distance, kernel-based metrics, or learned embeddings—could capture the non-linear attribute interactions observed in football. A hybrid approach might combine Euclidean distance for capability matching with cosine similarity for stylistic profiling, offering coaches multiple analytical lenses. Additionally, strategy-specific weighting of team–opponent ratios could capture the intuition that attribute differentials matter unequally across tactics: midfield control gaps are critical for possession-based systems but less relevant for direct counterattacking, whereas transition speed differentials show the reverse pattern.

**Multi-objective optimization.** Extending the model beyond semantic fit to incorporate physical risk indicators (fatigue accumulation, injury probability), expected-threat contributions, and coach-preference profiles (aggressive vs. conservative) would yield a richer decision landscape. Pareto-optimal strategy sets could be presented, allowing coaches to navigate trade-offs explicitly.

**Predictive simulation.** Incorporating Bayesian networks, Markov processes, or Monte Carlo simulations would enable *what-if* testing—evaluating alternative strategies and substitutions before committing. This would transform the DSS from a diagnostic tool into a predictive one, supporting pre-match preparation as well as in-game decisions.

**Interactive coaching interface.** A dashboard integrating radar charts, sensitivity curves, and robustness metrics—with sliders for coach-defined preferences (risk level, pressing intensity, possession–transition balance)—would support real-time, minute-by-minute strategy updates. Natural-language explanations (“why this strategy is recommended now”) and counterfactual exploration (“what if we substitute player X?”) would bridge the gap between analytical depth and operational usability.

**Validation with professional data.** Transitioning from simulated tests to real competitions using professional datasets would provide rigorous external validation. Concrete KPIs—expected goals conceded, shot quality, pressing recoveries—could benchmark DSS recommendations against actual coaching decisions, quantifying added value and identifying failure modes.

**Extension to other team sports.** The semantic-distance paradigm is not football-specific. Any domain where heterogeneous agents pursue collective objectives against an adaptive opponent admits the same formalization: a shared attribute space, a library of strategy templates, and a distance metric modulated by contextual pressure. Candidate sports include basketball, rugby, American football, ice hockey, and water polo. Of particular interest are *mixed human–robotic*

*teams*, such as those competing in RoboCup leagues, where artificial players exhibit well-defined, quantifiable capability profiles that map naturally onto macro-attribute vectors.

**From strategy selection to strategy synthesis.** The current DSS recommends a single best-matching strategy, but real tactical situations often call for *hybrid* approaches blending elements from multiple templates. Recent work on entangled heuristics for agent-augmented strategic reasoning [6] offers a natural extension: when several strategies achieve similar semantic distances, the system could *compose* them via interference-weighted fusion rather than selecting one. That framework models heuristics not as mutually exclusive options but as semantically interrelated potentials synthesized into novel formulations. Transposing this logic to football, a team whose profile activates both “Build-up Play” and “Fast Counterattack” might receive a composed recommendation: *controlled possession in midfield with rapid vertical transitions when space opens*—a hybrid that neither template captures alone.

**Adversarial and security domains.** Beyond cooperative sports, the methodology extends to explicitly *unfriendly* scenarios. Recent work on multi-drone urban defence [17] models the problem as a Sequential Stackelberg Security Game sharing structural parallels with ours: spatial decomposition, capability-based profiling, utility-driven strategy selection, and a probabilistic presence parameter analogous to our context weights. Our semantic-matching approach could complement such game-theoretic methods by guiding within-zone resource deployment when defender assets are heterogeneous. This synergy suggests a broader research programme applying explainable, profile-based decision support to hybrid human–AI security systems.

By combining semantic distance computation with diagnostic interpretability, the DSS supports complex tactical decisions without replacing coaching expertise—it amplifies it. With continued development in data automation, predictive simulation, and cross-domain generalization, systems of this kind may soon serve not only professional sports but also defence, robotics, and any setting where heterogeneous teams must coordinate adaptively against strategic adversaries.

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