FC Barcelona Defensive Fault Lines

Interpretation Document — More than a Hack 2026

An analytical system that identifies defensive vulnerabilities in FC Barcelona matches using time-series event data, Bayesian pattern detection, and LLM-assisted tactical explanations. Built on Metrica Sports Smart Tagging data across 11 matches.

> **Tactical Question:** *When and how does Barcelona's defensive structure break down, and which vulnerability patterns recur across matches?*

Scope: Scope 2 (Game modeling and pattern detection) with elements of Scope 1 (Interpretation) and multi-match comparative analysis.

Contents

1. Data Sources and Limitations

1.1 Available Data Per Match

Source	Format	Content	Coverage
Smart Tagging	*_pattern.xml	Team-level tactical phases: BUILD UP, PROGRESSION, CREATING CHANCES, etc.	Full match, both teams
ATD Metadata	*_FifaData.xml	Team names, player track IDs, pitch dimensions, frame rate	Complete metadata
ATD Positions	*_FifaDataRawData.txt	Per-frame x/y/speed for ball + player tracks	Ball: good. Outfield players: mostly NaN
Broadcast Video	*.mp4	Full match recording	All 11 matches

1.2 Critical Limitation: Tracking Sparsity

The ATD tracking feed provides position data generated from broadcast camera footage. Because broadcast cameras follow the ball, players frequently go off-screen, resulting in NaN values. Additionally, the ATD is team-level (no player identifiers) with identity fragmentation (40-60 extra IDs per match). This means:

- Individual player metrics (progressive carries, press resistance) are **not feasible**
- Defensive shape, compactness, or line height **cannot be determined** from tracking
- Ball position is usable and provides limited spatial context
- The system is built primarily on **team-level event phase data**

1.3 Smart Tagging Event Codes

Event Code	Description	Risk Weight (Opp / Barca)
GOALS	Goal scored	10 / 0
BALL IN THE BOX	Ball enters penalty area	8 / 0
CREATING CHANCES	Clear goal-scoring opportunity	7 / 0
BALL IN FINAL THIRD	Ball in attacking third	5 / 0
ATTACKING TRANSITION	Counter-attack initiated	4 / 0
PROGRESSION	Ball advanced through lines	3 / 0
SET PIECES	Corner, free kick, throw-in	3 / 0
DEFENDING IN DEF. THIRD	Defending near own goal	0 / 4
DEFENSIVE TRANSITION	Losing possession, recovering	0 / 3
DEFENDING IN MID. THIRD	Defending in middle third	0 / 2

Event Code	Description	Risk Weight (Opp / Barca)
DEFENDING IN ATK. THIRD	High press / defending forward	0 / 1
LONG BALL	Direct long-distance pass	0 / 0
BUILD UP	Possession from own half	0 / 0
PLAYERS IN THE BOX	Attackers in penalty area	0 / 0

Note: Smart Tagging is not manually ground-truthed. It may contain false positives and negatives.

1.4 Project Pivot

The original concept was individual player performance analysis. Due to tracking identity fragmentation and sparse position data, we pivoted to team-wide defensive analysis — a question fully answerable from the Smart Tagging data, which is clean and complete.

2. Methodology: Risk Scoring Pipeline

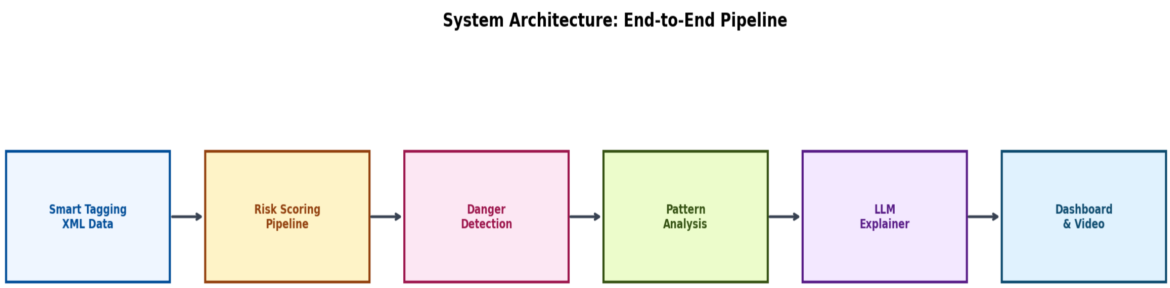

Figure 1: System Architecture — End-to-End Pipeline

The pipeline converts raw Smart Tagging annotations into a continuous per-second risk score (0-100) for each match. The end-to-end flow is: Smart Tagging XML -> Risk Scoring -> Danger Detection -> Pattern Analysis -> LLM Explanation -> Dashboard with Video Seek.

2.1 Time Grid and Raw Score

Events are converted to integer seconds. For each second of the match, we identify all active events and sum their risk weights. Opponent attacking events contribute positive risk; Barca defensive-phase events add additional risk (being in DEFENDING IN DEFENSIVE THIRD means the team is under pressure). Multiple overlapping events compound — this captures the combinatorial danger of simultaneous attacking and defensive breakdowns.

2.2 Smoothing and Normalization

Raw scores are smoothed with a 15-second centered rolling mean to prevent artificial drops when events end. Scores are normalized to 0-100 against the theoretical maximum (sum of all non-GOALS weights = 30). This means:

- Dangerous play without a goal tops out around 70-80
- Only a GOALS event (+10) can push the score toward 100
- Goal moments are spiked to 100 in the final 5 seconds of the GOALS annotation window

2.3 Design Rationale

The weight system is intentionally transparent and interpretable. Each weight reflects the proximity-to-goal of the tactical phase: events closer to the goal (BALL IN THE BOX, CREATING CHANCES) receive higher weights than upstream events (PROGRESSION, BUILD UP). This produces risk scores that align with coaching intuition — sustained pressure in the final third creates higher risk than possession in midfield.

3. Danger Moment Detection

Danger moments are identified using scipy's find_peaks algorithm on the risk timeline.

3.1 Detection Parameters

Parameter	Value	Purpose
Peak percentile	70th	Dynamic threshold — peaks must exceed this
Threshold floor	40.0	Absolute minimum (avoids trivial peaks)
Min distance	35 sec	Minimum gap between detected peaks
Prominence	10.0	Peak must rise 10+ above surrounding baseline
Goal lookback	90 sec	Search window for risk peak before a goal
Merge window	60 sec	Merge peaks within 60s into one sustained spell

These parameters were tuned using a grid search across all 11 matches, optimizing for: reasonable peak count per match (~10-20), window lengths between 20-60 seconds, and 100% goal coverage.

3.2 Severity Classification

Severity	Score Range	Meaning
Critical	85-100	Goal conceded or near-certain opportunity
High	70-84	Clear danger, multiple threatening events
Moderate	40-69	Elevated risk, territorial opponent advantage

3.3 Goal Anchoring

Every goal conceded is guaranteed to appear as a critical danger moment. The system looks back 90 seconds from the goal timestamp and takes the max-risk point. If within 5 seconds of an existing peak, it is promoted rather than duplicated. This ensures 100% goal coverage.

3.4 Merge Logic

Peaks within 60 seconds of each other are merged into a single sustained pressure spell. The merged moment keeps the highest peak score, the widest window, the union of active codes, and the maximum severity.

4. Match-by-Match Findings

4.1 Overview

The pipeline processed 11 FC Barcelona matches, detecting **144 danger moments** across all matches.

Statistic	Value
Total matches analyzed	11
Total goals: Barca scored	32
Total goals: Opponents scored	17
Total danger moments detected	144
Critical severity	21 (14.6%)
High severity	22 (15.3%)
Moderate severity	101 (70.1%)
Goal-anchored moments	17/17 (100% coverage)
Average danger moments per match	13.1

4.2 Match-by-Match Breakdown

#	Opponent	Score	Dangers	Crit	High	Mod	Goal-Anch	Avg Risk
1	AC Milan (A)	1-0	15	0	2	13	0	10.7
2	Arsenal (A)	3-5	22	6	1	15	5	12.6
3	AC Milan (H)	2-2	10	2	1	7	2	6.5
4	AS Monaco (H)	0-3	12	5	3	4	3	9.4
5	Como (H)	5-0	13	0	2	11	0	8.3
6	Man City (H)	2-2	20	3	5	12	2	14.5
7	Real Madrid (H)	3-0	21	0	3	18	0	13.3
8	Daegu FC (A)	5-0	3	0	1	2	0	3.0
9	FC Seoul (A)	7-3	10	3	1	6	3	6.4
10	Real Madrid (A)	2-1	15	1	2	12	1	9.3
11	Vissel Kobe (A)	3-1	3	1	1	1	1	4.8

(H) = Home, (A) = Away

4.3 Key Observations

High-danger matches: The Arsenal (5-3) and Manchester City (2-2) matches produced the most danger moments (22 and 20 respectively), reflecting their quality as opponents and the open, transitional nature of those games.

Monaco (0-3) — worst defensive performance: Despite only 12 danger moments, 5 were critical and all 3 goals were captured. The high critical-to-total ratio (42%) indicates concentrated, lethal attacks rather than sustained pressure.

Dominant wins still produce risk: Even in the 5-0 wins (Como, Daegu), the system detected moderate danger moments — consistent with the reality that even dominant teams face occasional counter-attacks or set-piece threats.

Real Madrid (3-0 win) — high moderate count: 21 danger moments with 0 critical suggests a match where Barcelona controlled the outcome but faced consistent mid-level pressure.

4.4 Visualizations

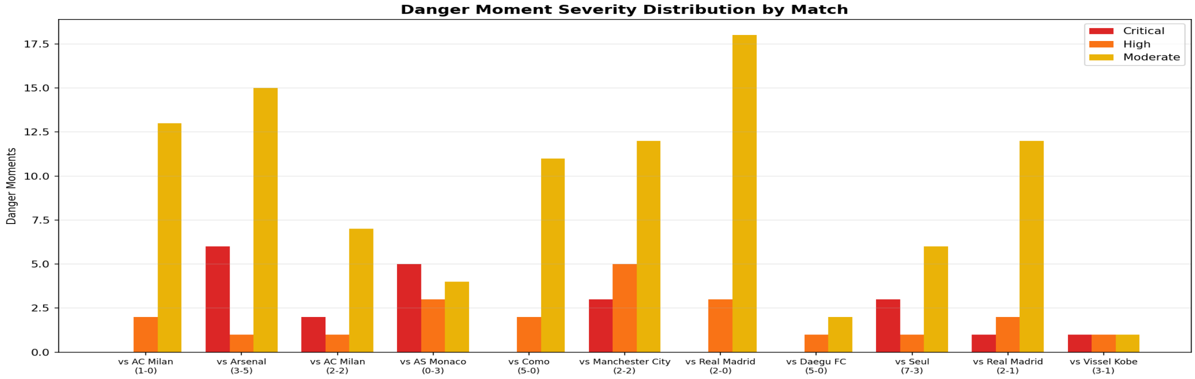

Figure 2: Danger Moment Severity Distribution by Match

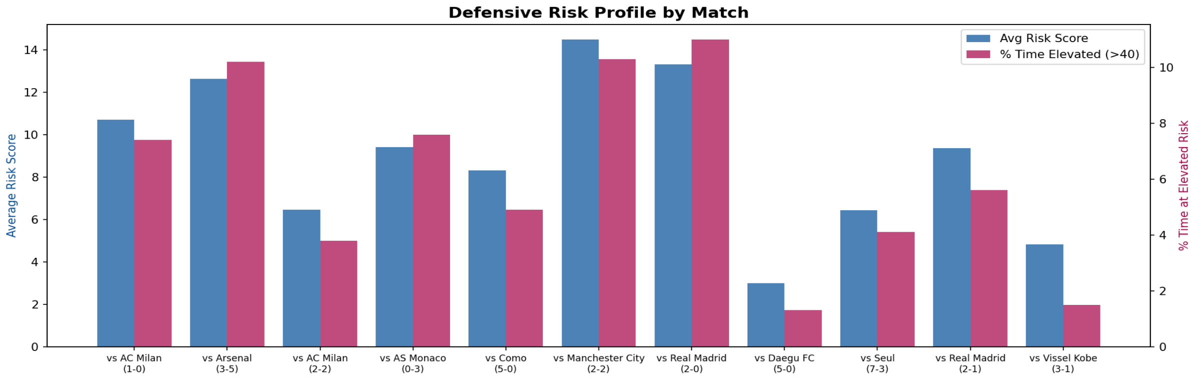

Figure 3: Defensive Risk Profile by Match — Average Risk and % Time at Elevated Risk

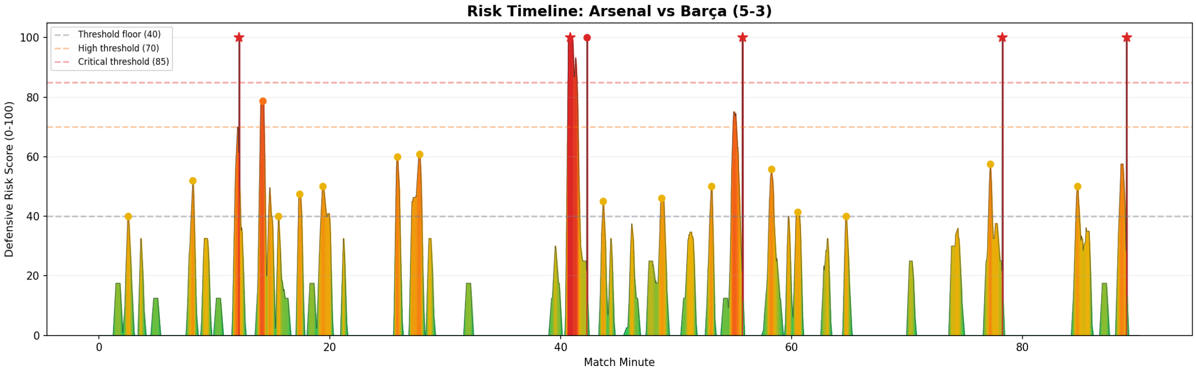

Figure 4: Risk Timeline — Arsenal vs Barca (5-3). Stars = goal-anchored moments. Color gradient: green (low) to red (high). Dashed lines = severity thresholds.

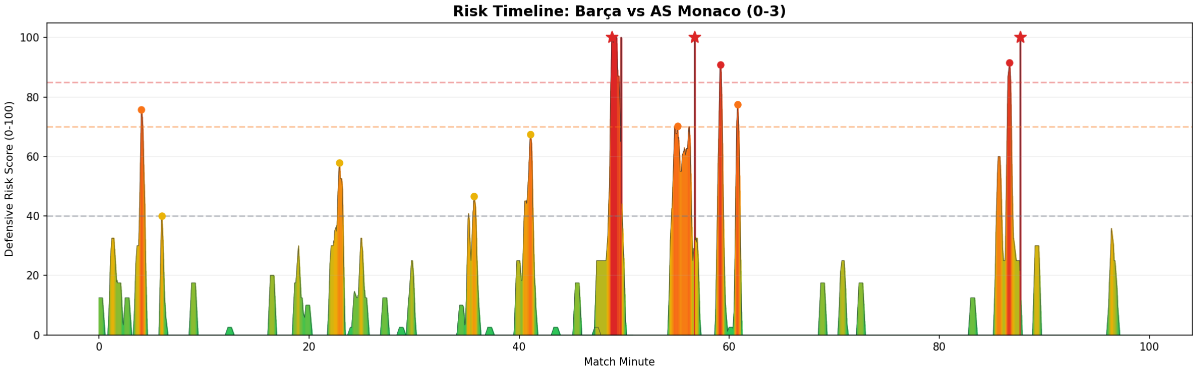

Figure 5: Risk Timeline — Barca vs AS Monaco (0-3). All 3 goals occurred in the second half, with 5 critical moments concentrated after halftime.

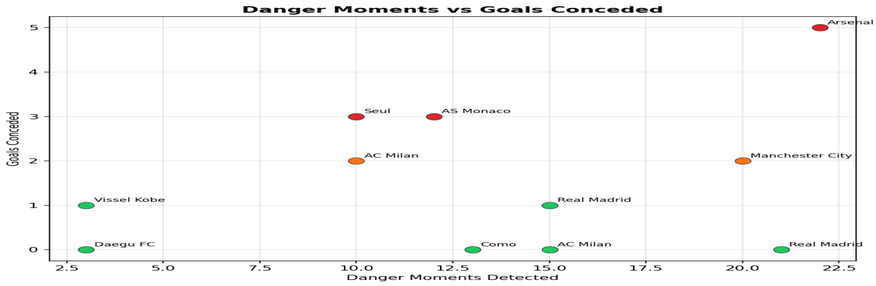

Figure 6: Danger Moments vs Goals Conceded — correlation between system output and actual results.

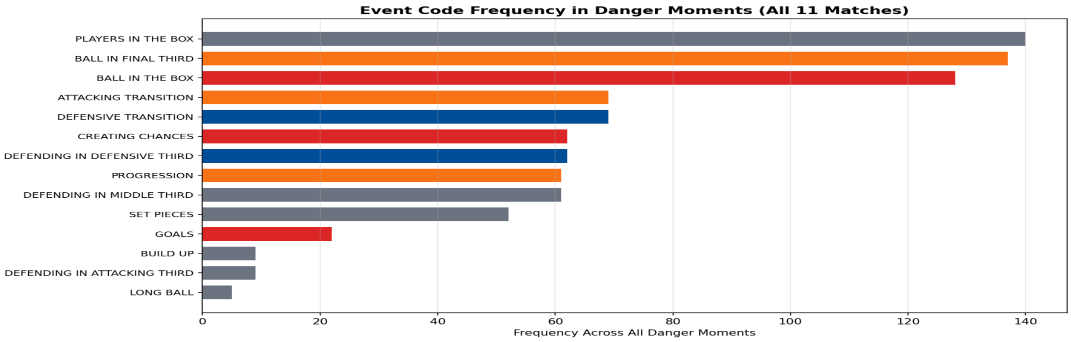

Figure 7: Event Code Frequency in Danger Moments (All 11 Matches)

4.5 Event Code Frequency in Danger Moments

Event Code	Frequency	% of Danger Moments
PLAYERS IN THE BOX	140	97.2%
BALL IN FINAL THIRD	137	95.1%
BALL IN THE BOX	128	88.9%
ATTACKING TRANSITION	69	47.9%
DEFENSIVE TRANSITION	69	47.9%
CREATING CHANCES	62	43.1%
DEFENDING IN DEF. THIRD	62	43.1%
PROGRESSION	61	42.4%
DEFENDING IN MID. THIRD	61	42.4%
SET PIECES	52	36.1%

The near-universal presence of PLAYERS IN THE BOX and BALL IN FINAL THIRD validates the weight system. The 48% co-occurrence of ATTACKING TRANSITION and DEFENSIVE TRANSITION highlights transition play as a primary vulnerability vector.

4.6 Half-by-Half Vulnerability Distribution

Period	Danger Moments	Critical	Goals Conceded
1st Half	76 (52.8%)	10	8
2nd Half	68 (47.2%)	11	9

The distribution is nearly balanced, with a slight first-half bias in total dangers (76 vs 68). However, critical moments and goals are marginally higher in the second half. **Notable:** Monaco went from 0 critical in H1 to 5 critical in H2 (all 3 goals).

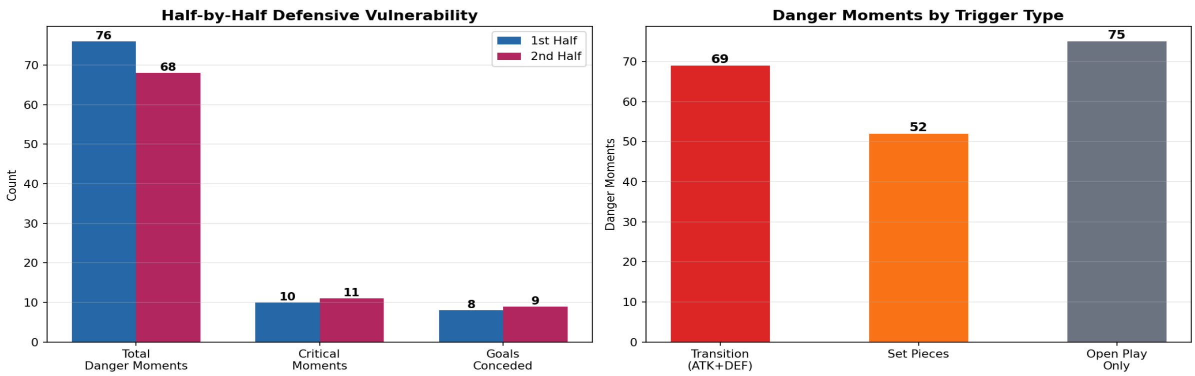

Figure 8: Half-by-Half Vulnerability and Danger Trigger Type Distribution

4.7 Transition Play: The Primary Vulnerability Vector

Transition moments (ATTACKING TRANSITION + DEFENSIVE TRANSITION) are present in **47.9% of all danger moments** (69/144) and account for **29.4% of goals conceded** (5/17). Set pieces are involved in **36.1% of danger moments** (52/144) and **23.5% of goals** (4/17). The remaining danger moments arise from sustained positional attacks.

4.8 Deep Dive: Most Dangerous Matches

Arsenal (5-3) — highest total danger (22 moments, 6 critical): The most dangerous match in the dataset. Five goals captured as critical moments. Rapid transitions in both directions, with danger spread across both halves (12 in H1, 10 in H2) — sustained vulnerability, not a single-half collapse.

AS Monaco (0-3) — most concentrated lethality: Despite only 12 total danger moments, Monaco achieved a 42% critical rate. All danger escalated in the second half (0 critical in H1, 5 in H2). This suggests Monaco's half-time tactical adjustment was decisive.

Manchester City (2-2) — highest sustained pressure: 20 danger moments with a match-leading average risk of 14.5. The first half was especially intense (16 of 20 dangers).

5. Cross-Match Pattern Analysis

5.1 Fingerprinting Methodology

For each danger moment, we extract a **fingerprint**: the sequence of event codes that newly entered the active set during the preceding 60 seconds. Codes are filtered by stopwords (removing ubiquitous codes like BALL IN FINAL THIRD), deduplicated while preserving order, and compressed to the top 4 by weight. Fingerprints are clustered using subsequence similarity (threshold 0.85). Patterns must appear in 2+ matches with 3+ occurrences and lift of 1.15+ over baseline.

5.2 Bayesian Confidence Scoring

Each pattern's goal rate is modeled as Bernoulli with a Beta(1,1) prior. The composite confidence score = P(pattern_rate > baseline_rate) x support_scaler.

Tier	Score	Coaching Guidance
High	>= 0.70	Recurring vulnerability. Address in tactical sessions.
Medium	0.45-0.69	Notable pattern. Monitor in upcoming matches.
Low	< 0.45	Candidate theme. Insufficient evidence to act on.

5.3 Detected Patterns

The pattern analyzer identified **3 recurring vulnerability patterns** across the 11 matches:

Pattern 1: ATTACKING TRANSITION -> DEFENSIVE TRANSITION

Confidence: 0.601 (Medium) | **Lift:** 2.66x baseline | **Occurrences:** 10 (3 resulted in goals) | **Matches:** Arsenal (5-3), AC Milan (2-2), FC Seoul (3-7)

This pattern captures moments where Barcelona loses the ball during an attacking move and the opponent immediately launches a counter-attack. The rapid transition from attack to defense — with players caught upfield — creates the most dangerous vulnerability in the dataset. The 2.66x lift means this sequence is nearly 3 times more likely to result in a goal.

Pattern 2: CREATING CHANCES -> DEFENDING IN DEFENSIVE THIRD

Confidence: 0.471 (Medium) | **Lift:** 1.97x baseline | **Occurrences:** 9 (2 resulted in goals) | **Matches:** Arsenal (5-3), AS Monaco (0-3)

This captures situations where the opponent's chance creation directly pushes Barcelona into deep defending. The mid-block is bypassed — the opponent progresses from creating chances to box-area threats without an intermediate defensive phase, indicating a structural gap.

Pattern 3: PROGRESSION -> DEFENDING IN MIDDLE THIRD

Confidence: 0.463 (Medium) | **Lift:** 1.48x baseline | **Occurrences:** 12 (2 resulted in goals) | **Matches:** AS Monaco (0-3), FC Seoul (3-7)

Opponent progression through midfield while Barcelona is defending in the middle third. This pattern appeared in both heavy-defeat matches, indicating that when Barcelona's midfield pressing is ineffective, the defensive line is exposed.

5.4 Baseline Statistics

Metric	Value
Total danger moments with valid fingerprints	144
Baseline goal rate (any danger moment -> goal)	11.8%
Pattern 1 goal rate	30.0% (2.66x baseline)
Pattern 2 goal rate	22.2% (1.97x baseline)
Pattern 3 goal rate	16.7% (1.48x baseline)

6. LLM Integration

The system uses GPT-4o-mini (via OpenRouter) to transform structured evidence packs into natural-language tactical explanations. The LLM never sees raw data — only curated context.

6.1 Prompt Architecture

Template	Input	Output
Moment prompt	Active codes, risk score, severity, goal flag	3-5 sentence tactical explanation with [CODE] refs
Window prompt	Events in 5-min window, avg risk, team breakdown	Tactical summary of passage of play
Pattern prompt	Sequence, frequency, confidence stats	Structural vulnerability explanation + recommendations

6.2 Example LLM Outputs

Example 1 — High severity, open play: AC Milan vs Barca (0-1), 37:01-37:46, risk 77.17

> *"During the critical window from 37:01 to 37:46, Barcelona's defensive structure appeared to falter primarily due to poor organization during the [DEFENSIVE TRANSITION]. As AC Milan initiated an [ATTACKING TRANSITION], Barcelona's players were slow to regroup, leading to unmarked opposition players in the [FINAL THIRD]. The lack of effective communication and commitment to closing down space in the [DEFENDING IN DEFENSIVE THIRD] allowed Milan to create multiple [BALL IN THE BOX] scenarios. To address these vulnerabilities, the coaching staff should emphasize rapid defensive recovery drills and reinforce the importance of spatial awareness during transitions."*

Example 2 — Moderate severity, set piece: AC Milan vs Barca (0-1), 28:32-29:30, risk 50.0

> *"FC Barcelona faced a considerable threat due to failures in managing defensive transitions [DEFENSIVE TRANSITION] and positioning during attacks by AC Milan. The combination of ball in the box situations [BALL IN THE BOX] and set pieces [SET PIECES] indicates a lack of effective marking and organization during dead-ball scenarios. Coaches should emphasize the importance of maintaining shape during transitional phases and implementing stricter protocols for player positioning during set pieces."*

Note how the LLM produces different explanations tailored to each event combination: Example 1 focuses on transition recovery speed, while Example 2 identifies set-piece marking as the primary issue.

6.3 Hallucination Mitigation

- **Data-limitation-aware system prompt:** Explicitly tells the LLM what data IS and IS NOT available. States that events are team-level, preventing fabrication of individual player actions.
- **Code citation requirement:** Event codes must be cited in [BRACKETS], making analysis verifiable against the evidence pack.
- **Confidence-gated language:** Only patterns with confidence >= 0.60 are called 'recurring.' Lower-confidence patterns are hedged as 'candidate themes to monitor.'

- **Caching:** All LLM responses are cached (SHA-256 of prompt -> JSON file). Identical evidence packs produce identical explanations, ensuring reproducibility.

7. Interactive Dashboard

A React + FastAPI dashboard allows coaching staff to explore the analysis interactively:

- **Match selector:** Choose from all 11 matches
- **Risk timeline chart:** Color-coded risk score over match time with goal markers
- **Danger moment list:** Clickable cards ranked by severity with LLM explanations
- **Video seek:** Click a danger moment to jump to the corresponding broadcast timestamp
- **Custom window analysis:** Click two points on the timeline to get an LLM explanation of any passage of play

The dashboard connects to the FastAPI backend which computes risk scores on demand and caches results. Video offset calibration (pre-match broadcast time, halftime extra time) is stored per match to enable accurate video seeking.

8. Limitations and Honest Disclosure

8.1 What the System CAN Do

- Identify specific time windows where Barca was most defensively vulnerable
- Quantify danger severity on a 0-100 scale with three tiers
- Detect recurring event sequences preceding danger across matches
- Provide Bayesian confidence levels for pattern recurrence
- Generate LLM explanations constrained to available evidence
- Link danger moments to broadcast video timestamps

8.2 What the System CANNOT Do

- Attribute defensive failures to **individual players** (events are team-level)
- Analyze defensive shape, compactness, or pressing structure (tracking too sparse)
- Compute player-level xG, progressive carries, or dribble success rates
- Determine **causal** relationships (patterns are correlational)
- Replace expert coaching judgment — the system is an analytical aid

8.3 LLM Output Caveats

LLM explanations are constrained to the evidence pack but are not infallible. Subtle inference errors may occur. All outputs should be reviewed by coaching staff before informing tactical decisions.

8.4 Sample Size

With 11 matches, pattern analysis has limited statistical power. Patterns appearing in 2-3 matches may be coincidental. The Bayesian framework accounts for this (small sample -> wide credible intervals -> lower confidence), but coaches should treat medium/low confidence patterns as hypotheses, not confirmed weaknesses.

8.5 Smart Tagging Accuracy

Smart Tagging data is not manually ground-truthed. It is inferred through automated processes and may contain both false positives and false negatives. The risk engine inherits any labeling errors.

9. Coaching Recommendations

- **Transition vulnerability (Pattern 1, confidence 0.60):** The ATTACKING TRANSITION -> DEFENSIVE TRANSITION pattern is the strongest signal. When Barcelona loses possession during attacks, recovery is insufficient. Rapid defensive recovery drills and positional discipline when committing players forward should be prioritized.
- **Mid-block bypass (Pattern 2, confidence 0.47):** Opponents who create chances tend to quickly reach Barcelona's defensive third without an intermediate phase. Reviewing pressing triggers and compactness between lines would address this.
- **Midfield progression control (Pattern 3, confidence 0.46):** When opponents successfully progress through midfield, danger escalates. Strengthening the midfield press and ensuring defensive cover during transitions would reduce this pattern.
- **Second-half resilience:** The Monaco match (0 -> 5 critical in H2) suggests opponent half-time adjustments can be devastating. Reviewing half-time tactical communication is recommended.
- **Use the video linkage:** Every danger moment maps to a broadcast timestamp. Review footage alongside the LLM explanation for the richest analytical context.
- **Monitor patterns in future matches:** All three detected patterns are at medium confidence. Track whether they appear in subsequent matches.

10. Suggestions for Metrica Nexus

- **Smart Tagging timeline offset tool:** Provide users with the option to offset timestamps so they match in-game time. Users would input the 4 key offset times per match.
- **Player ID merging:** Allow users to merge fragmented player IDs in tracking data and connect them to known player names or external databases.
- **Player recognition confidence scores:** Include confidence values when correlating different player IDs, enabling analysts to assess reliability of player-level metrics.

11. Conclusion

This project demonstrates that meaningful tactical intelligence can be extracted from team-level Smart Tagging data alone, even without complete tracking data. The Defensive Fault Lines system transforms 11 matches of event annotations into a continuous risk timeline, detects 144 danger moments with 100% goal coverage, identifies 3 recurring vulnerability patterns with Bayesian confidence scoring, and produces LLM-assisted tactical explanations grounded in verifiable evidence.

The key tactical finding is that transition play is Barcelona's primary vulnerability vector, appearing in nearly half of all danger moments and producing the highest-lift pattern in the dataset. The system provides an analytical foundation that coaching staff can use alongside their own observations, with every insight traceable to specific match moments, event codes, and broadcast timestamps.

This document was generated programmatically. Tactical explanations within the system are assisted by GPT-4o-mini (via OpenRouter). All statistical analysis, risk scoring, pattern detection, and verification logic is deterministic Python code.