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	Full match, both teams
ATD Metadata	*_FifaData.xml	Team names, player IDs, pitch dims	Complete metadata
ATD Positions	*_FifaDataRawData.txt	Per-frame x/y/speed	Ball: good. Outfield: partial
Parsed Tracking	player_positions.csv + ball_positions.csv	Per-match player/ball positions with team ID mapping	All 11 matches (custom parser)
Broadcast Video	*.mp4	Full match recording	All 11 matches

1.2 Critical Limitation: Tracking Sparsity

The ATD tracking feed provides position data from broadcast camera footage. Because cameras follow the ball, players frequently go off-screen, resulting in NaN values. The ATD has 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**

Tracking data recovery: Despite these limitations, we built a custom batch parser (tracking_batch_parser.py) that extracts usable ball positions and partial player positions from the raw ATD feed across all 11 matches. The parsed tracking data is stored as player_positions.csv and ball_positions.csv per match, with team ID mapping (team_map.json) to identify which tracks belong to Barcelona vs. the opponent.

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
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

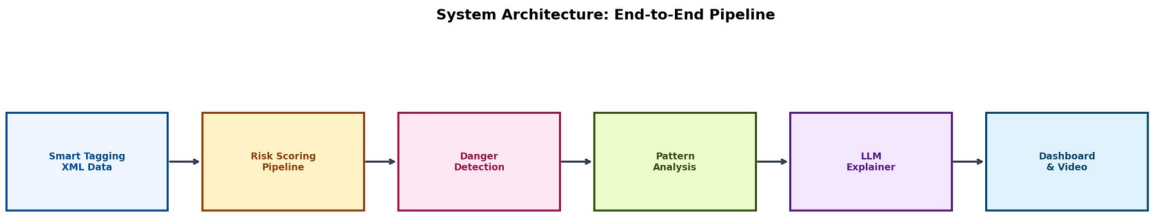

Figure 1: System Architecture — End-to-End Pipeline

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. 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. Scores are normalized to 0–100 against the theoretical maximum (sum of all non-GOALS weights = 30):

- 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.

2.4 Spatial Feature Extraction from Tracking Data

For each danger moment, the system extracts a spatial snapshot from the parsed tracking data (tracking_features.py). At the peak timestamp of each danger window, the system computes:

- **Team shape metrics:** Width, length, and centroid position for both Barcelona (defending) and the opponent (attacking), computed from the 5th–95th percentile spread of player positions.
- **Ball proximity:** Nearest defender and nearest attacker distance to the median ball position within the window.
- **Ball-side overload detection:** Within a configurable radius around the ball, the system counts defenders vs. attackers to identify numerical disadvantages.
- **Coverage diagnostics:** Each spatial snapshot includes a tracking_coverage_warning flag when fewer than 6 players per team are tracked, ensuring the LLM does not over-interpret sparse data.

These spatial features are passed as a structured JSON evidence pack alongside the event codes to the LLM, enabling spatially-grounded tactical explanations. The system includes interpretation rules in the LLM system prompt (e.g., distance thresholds: ≤0.05 = very tight, ≤0.12 = close, ≤0.25 = moderate, >0.25 = far) to prevent hallucination from spatial data.

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.

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

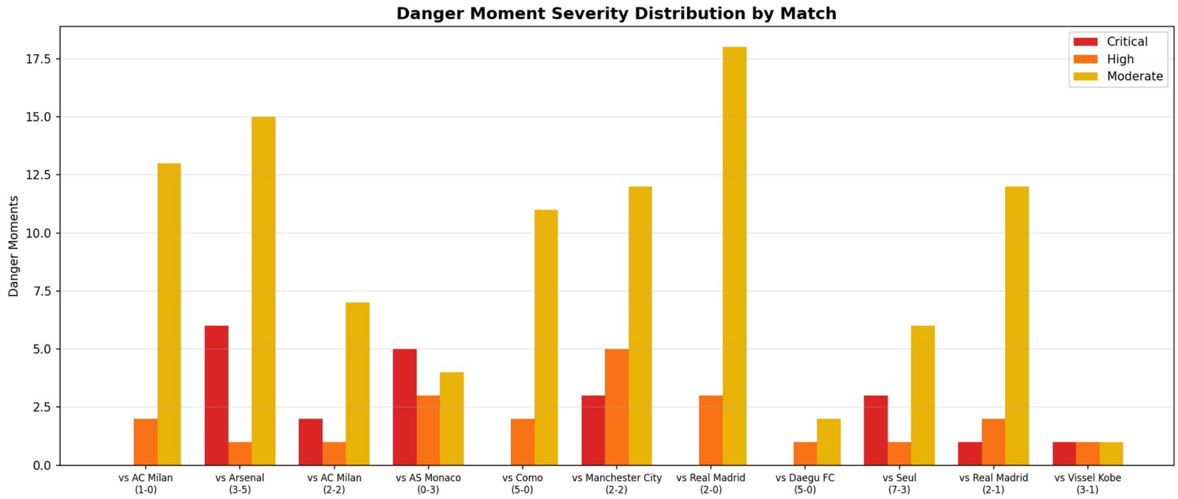

Figure 2: Danger Moment Severity Distribution by Match

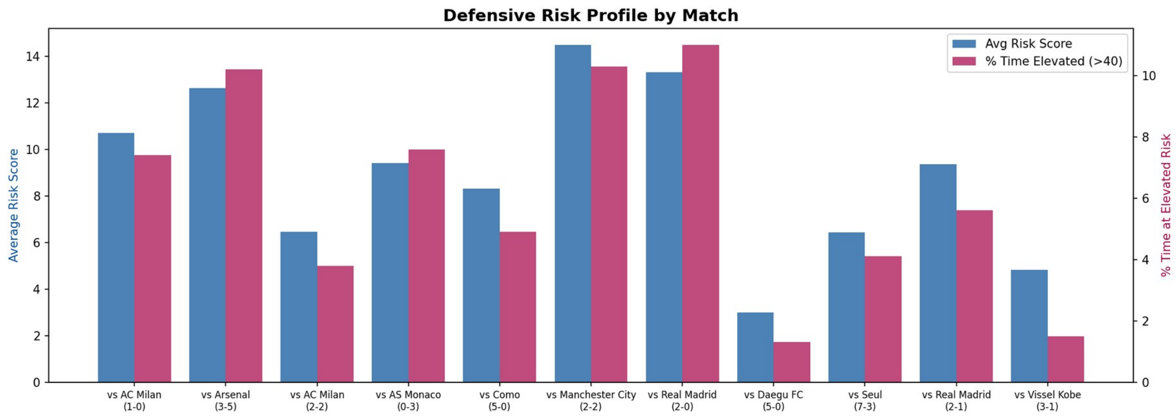

Figure 3: Defensive Risk Profile by Match — Average Risk and % Time at Elevated Risk

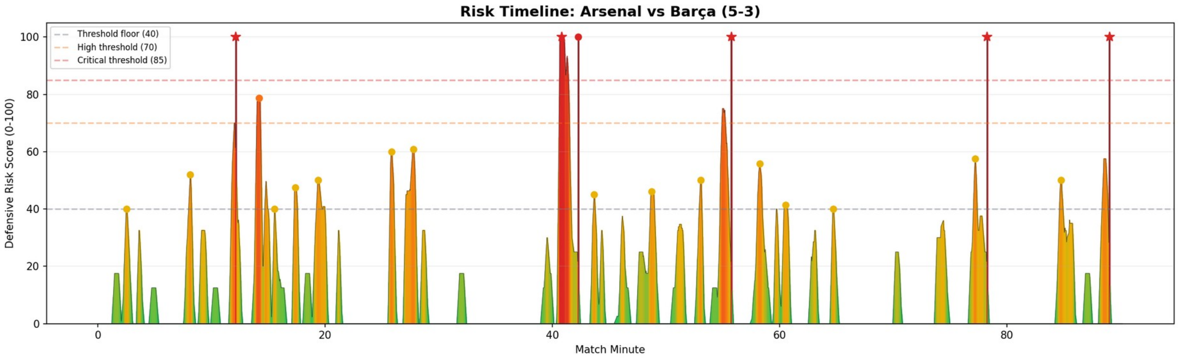

Figure 4: Risk Timeline — Arsenal vs Barca (5-3). Stars = goal-anchored moments.

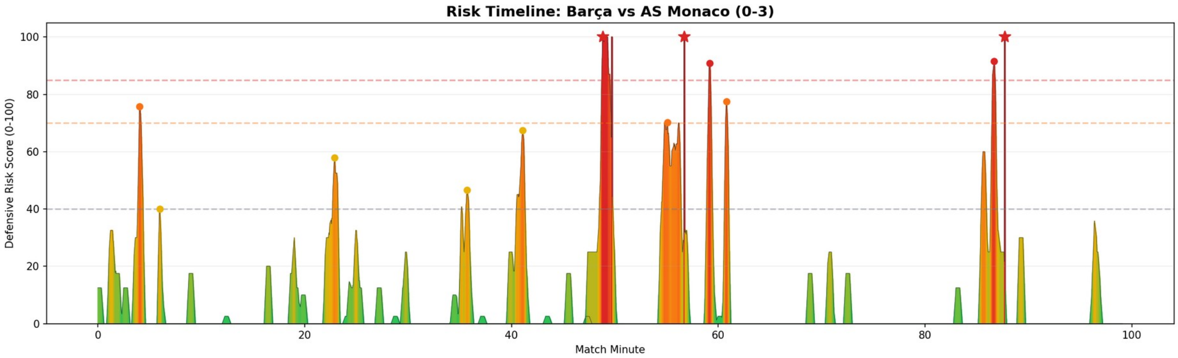

Figure 5: Risk Timeline — Barca vs AS Monaco (0-3). All 3 goals in the second half.

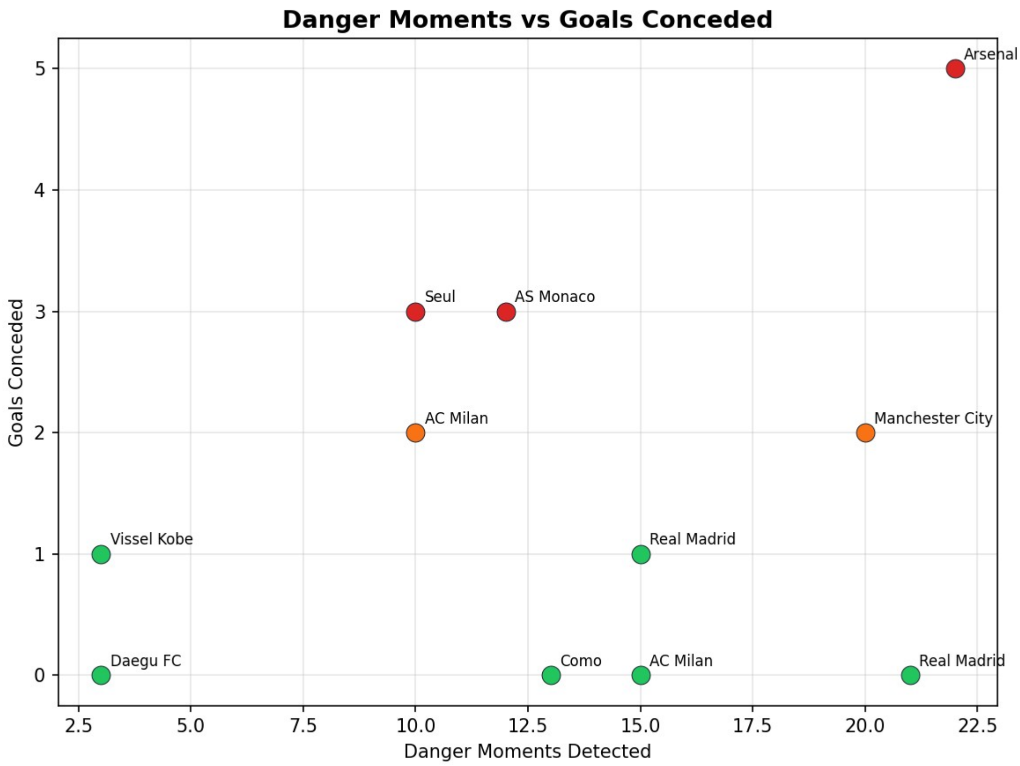

Figure 6: Danger Moments vs Goals Conceded — correlation between system output and results.

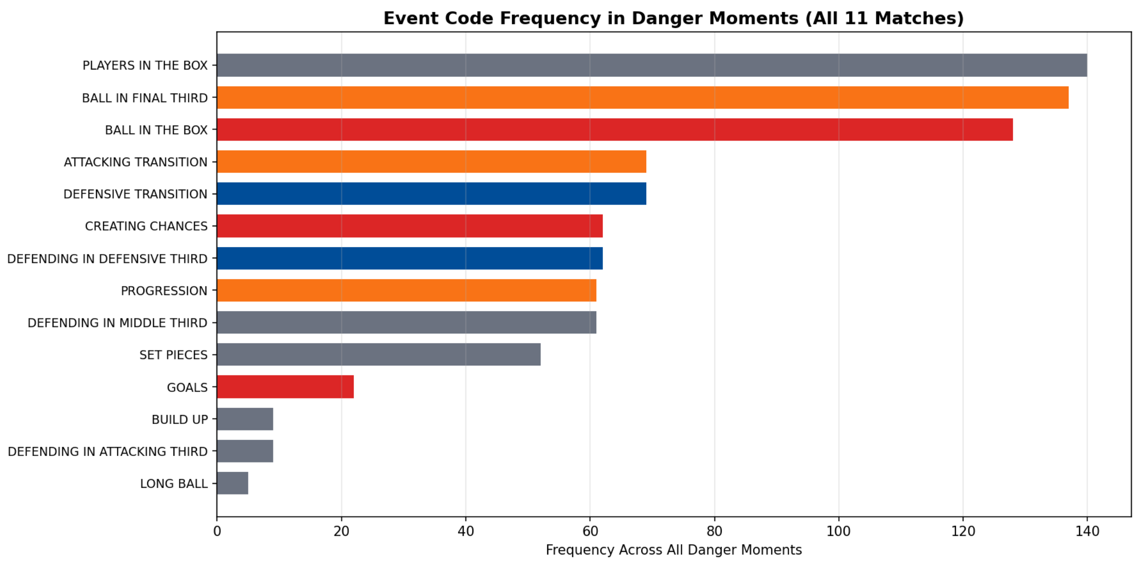

Figure 7: Event Code Frequency in Danger Moments (All 11 Matches)

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 transitions 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

Notable: Monaco went from 0 critical in H1 to 5 critical in H2 (all 3 goals conceded).

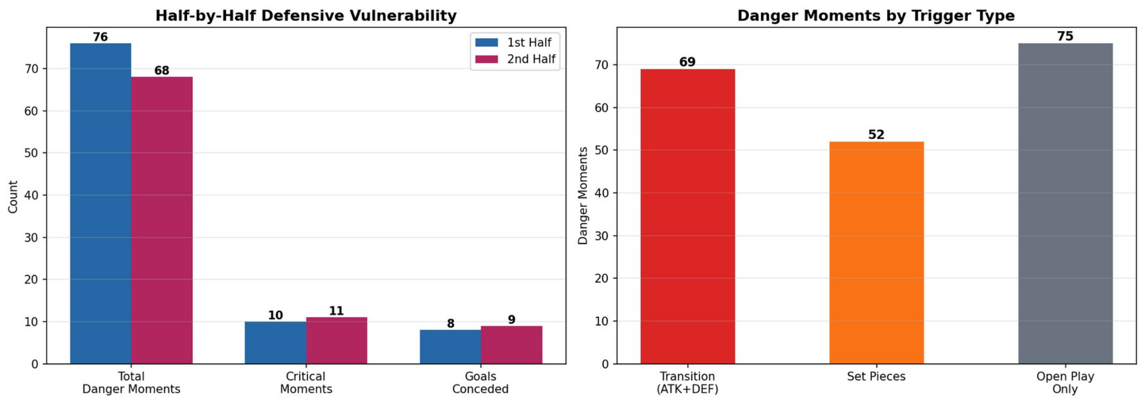

Figure 8: Half-by-Half Vulnerability and Danger Trigger Type Distribution

4.7 Transition Play: The Primary Vulnerability Vector

Transition moments 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).

4.8 Deep Dive: Most Dangerous Matches

Arsenal (5-3) — highest total danger (22 moments, 6 critical): The most dangerous match in the dataset. 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: 42% critical rate. All danger escalated in the second half (0 critical H1, 5 critical H2). Monaco's half-time adjustment was decisive.

Manchester City (2-2) — highest sustained pressure: 20 danger moments with match-leading average risk of 14.5. First half 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, 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 ≥1.15.

5.2 Bayesian Confidence Scoring

Each pattern's goal rate is modeled as Bernoulli with a Beta(1,1) prior. Composite confidence score = P(pattern_rate > baseline_rate) × 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:** 2.66× | **Occurrences:** 10 (3 goals) | **Matches:** Arsenal, AC Milan (H), FC Seoul

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. The 2.66× 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:** 1.97× | **Occurrences:** 9 (2 goals) | **Matches:** Arsenal, AS Monaco

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:** 1.48× | **Occurrences:** 12 (2 goals) | **Matches:** AS Monaco, FC Seoul

Opponent progression through midfield while Barcelona defends 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% (2.66× baseline)
Pattern 2 goal rate	22.2% (1.97× baseline)
Pattern 3 goal rate	16.7% (1.48× 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 consisting of event codes, risk scores, and (where available) spatial tracking summaries with team shape, ball proximity, and overload metrics.

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.*

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.*

6.3 Hallucination Mitigation

- **Data-limitation-aware system prompt:** Explicitly tells the LLM what data IS and IS NOT available.
- **Code citation requirement:** Event codes must be cited in [BRACKETS], making analysis verifiable.
- **Confidence-gated language:** Only patterns with confidence ≥ 0.60 are called "recurring."
- **Tracking-aware interpretation rules:** The system prompt includes explicit distance thresholds and overload criteria. The LLM must cite coverage warnings when tracking data is sparse (<6 players tracked).
- **Caching:** SHA-256 of prompt → JSON file. Identical evidence packs produce identical explanations.

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 for on-demand LLM explanation

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
- Extract spatial snapshots from tracking data (team shape, ball proximity, overload detection) to ground LLM explanations

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. 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.

9. Coaching Recommendations

- **Transition vulnerability (Pattern 1, confidence 0.60):** Rapid defensive recovery drills and positional discipline when committing players forward should be prioritized.
- **Mid-block bypass (Pattern 2, confidence 0.47):** Reviewing pressing triggers and compactness between lines would address this.
- **Midfield progression control (Pattern 3, confidence 0.46):** Strengthening the midfield press and ensuring defensive cover during transitions.
- **Second-half resilience:** Monaco (0 → 5 critical in H2) suggests opponent half-time adjustments can be devastating.
- **Use the video linkage:** Every danger moment maps to a broadcast timestamp. Review footage alongside the LLM explanation.
- **Monitor patterns in future matches:** All three patterns are at medium confidence. Track whether they recur.

10. Suggestions for Metrica Nexus

- **Smart Tagging timeline offset tool:** Provide users with the option to offset timestamps so they match in-game time.
- **Player ID merging:** Allow users to merge fragmented player IDs in tracking data and connect them to known player names.
- **Player recognition confidence scores:** Include confidence values when correlating different player IDs.

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 are assisted by GPT-4o-mini (via OpenRouter). All statistical analysis, risk scoring, pattern detection, and verification logic is deterministic Python code.