

AI Playbook for Football Academies

Where artificial intelligence changes the decisions an academy makes, where it does not, and how to deploy it without harming the players or the institution.

WRITTEN FOR	Academy directors, sporting directors, chief executives, owners and investors, federations and national academies.
SCOPE	Professional-club academies and national talent programmes in Europe and the Middle East; boys' and girls' pathways alike.
BASIS	Published research, league and federation rules, vendor disclosures and the author's own analytical work. No client engagement is described or implied.

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ABOUT THIS DOCUMENT

What this playbook is, and what it is not

Purpose

Every football academy is now being sold artificial intelligence. Most of what is on offer is aimed at the wrong problem. This playbook sets out where AI genuinely improves the decisions an academy makes, where the evidence is thin, and how to build the foundations that make any of it worth doing. It is written for the people who sign the budgets and carry the responsibility, not for data scientists.

How to read it

Part I explains the academy as a system of decisions and puts numbers on it. Part II maps the use cases and gives a verdict on each. Part III describes the intelligence stack, with the decision ledger at its centre. Part IV treats regulation and safeguarding as design constraints. Part V provides a maturity model, a self-assessment and indicative budgets. Part VI is a ninety-day plan.

A reader with fifteen minutes should take the executive summary, the use-case map on page 10, the "do not deploy" list on page 17 and the ninety-day plan on page 26.

Evidence and sources

Figures are drawn from published research, from league, federation and FIFA rules, from public statements by clubs and vendors, and from the author's own analysis. Every benchmark carries a source, listed on page 28. Where a figure is the author's estimate rather than a measured benchmark, it is labelled as such. Vendor prices are vendor-reported and change frequently.

What it is not

- It is not legal advice. The regulatory sections summarise the position as at September 2026 and identify questions for counsel; classification of any specific system depends on its facts.
- It is not a vendor guide. Products are named only where a documented deployment illustrates a point. Naming is not endorsement, and omission is not criticism.
- It is not a claim of client work. The analysis is independently produced and does not describe any engagement with any academy, club or federation.
- It is not a manual for building models. It is a manual for deciding what to build, what to buy, and what to refuse.

A note on the word "AI"

Academies are offered three different things under one label: statistics applied to data they already hold; machine-learning models that classify or predict; and generative systems that retrieve, summarise and draft. The playbook keeps them apart, because their evidence, cost and regulatory position differ. Several of the highest-value recommendations here use the first category and would have been possible ten years ago. That is not a weakness of the argument. It is the argument.

EDITORIAL POSITION

The scarce asset in an academy is not data and it is not models. It is a reliable record of what was decided, why, with what information, and what happened next. Almost no academy has one. Building it is the first AI project, and it needs no AI.

VERSION

Edition 1.0, 1 September 2026. Corrections and later editions at jonsoler.com.

USE

May be shared in full within an organisation for internal discussion. Extracts should be attributed to Jon Soler, *AI Playbook for Football Academies* (2026).

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EXECUTIVE SUMMARY

Seven findings, and what to do first

- 01 The academy's competitive asset is decision quality, not data volume.** English academies have shared a central data platform since 2012; a former Premier League director of youth described it a decade later as rich in data but largely untapped.¹ Data that is never consulted at the moment of decision has no value.
- 02 Talent prediction is the weakest use case and the most heavily marketed.** Base rates are severe, single-academy samples are tiny, outcomes arrive a decade later, and the training labels are the club's own past selections. A model built on that history learns the academy's biases and then enforces them. Nothing that ranks children by future value should be bought.
- 03 The first project should be a selection-bias audit.** Across English academies, roughly half of all players are born in the first quarter of the selection year; one academy recorded no late-maturing players at all at U15 and U16; across twelve Scottish academies the bias towards early maturers appears at U12 and is large by U18.²⁻⁴ The audit uses data the academy already holds and takes weeks, not years.
- 04 Growth-aware load management is the highest-return operational use.** Injury incidence roughly doubles around peak height velocity and rises with growth rate.⁵⁻⁷ Software adds individual baselines and early warning; it does not add a reliable "injury risk score", whatever the brochure says.
- 05 Generative AI's value is institutional memory.** Sevilla FC's Scout Advisor retrieves and summarises more than two hundred thousand of the club's own scouting reports.⁸ The same pattern applied to an academy's reviews, plans and medical notes is the most useful generative deployment available, provided no personal data of minors ever enters a consumer tool.
- 06 Regulation is now a design constraint.** Under the EU AI Act, inferring players' emotions in training or educational settings has been prohibited since February 2025, and systems that support admission, evaluation or contract decisions fall into high-risk categories with obligations from 2 December 2027.⁹ Children's data protection applies today, in the EU, the UK and the Gulf.
- 07 In the Gulf the binding constraint is not screening scale.** Saudi Arabia's Mahd Academy reaches 1.7 million pupils and is piloting an AI discovery platform; Qatar's Aspire screened 3.5 million boys between 2007 and 2014.¹⁰⁻¹¹ Yet over twenty seasons Saudi Arabia and Qatar together appear as the training association of four players in Europe's five major leagues.¹² Value sits in development decisions and coach capacity, where AI supports rather than selects.

WHAT TO DO FIRST

Build the decision ledger. Run the bias audit. Put growth monitoring on a calendar. Choose one generative use case with a named workflow owner. Map every existing and proposed system against the AI Act and data-protection rules. Agree the "do not deploy" list at board level. All of it fits in ninety days (Part VI).

~50%

of players in English academies born in the first quarter of the selection year (48.6% and 54.8% in two studies)²⁻³

2×

injury incidence around peak height velocity compared with the pre-growth-spurt period in an English academy⁶

5.7

players per training club: 13,881 players in Europe's five major leagues over twenty seasons, from 2,424 training clubs¹²

2 Dec 2027

date from which the EU AI Act's high-risk obligations apply to stand-alone systems in education, vocational training and employment⁹

PART I

I

The academy as a decision system

An academy is usually described as a place: pitches, a school, a medical room, a car park full of parents. For the purpose of this playbook it is better described as a portfolio of decisions made under severe uncertainty, about children, over a horizon of ten to twelve years, with outcomes that are only known long after the people who made the decisions have moved on.

A professional-club academy typically registers between 150 and 250 players across ten or more age groups. Each season it makes a few hundred consequential calls: who enters, who stays, who is released, who plays up, who is rested, who is offered a scholarship, a first contract, a loan, a sale. Most are made in short meetings, from coach opinion and a handful of physical tests, by people who are competent, sincere and systematically biased in ways the research literature has documented for thirty years.

The financial variance sits at the end of the pipeline, in a handful of contract, loan and sale decisions. The distortions enter at the beginning, in intake and annual retention, where relatively older and earlier-maturing boys look better than they are and later developers are quietly removed. By the time the expensive decisions arrive, the pool from which they are made has already been narrowed by the cheap ones.

This is the frame in which artificial intelligence should be judged. The question is never "what can the technology do". It is "which decision does this improve, by how much, at what cost, and with what risk to a fourteen-year-old". Part I puts numbers on the system so that Part II can answer that question use case by use case.

FOUR PROPERTIES OF THE SYSTEM

Long feedback loops. The outcome of a decision at U12 is known, at best, at U21. Staff turnover is faster than that. Without a written record, the institution cannot learn.

Tiny samples. An academy that has existed for twenty years has produced a few dozen professionals. No statistical method rescues a dataset that small from the noise in it.

Circular labels. "Success" in the data is defined by the academy's own past choices: who was kept, who was given minutes. Models trained on that history learn the choices, not the talent.

Asymmetric harm. A wrong purchase in the first team costs money. A wrong release at fourteen costs a child a pathway and, occasionally, the club a player worth more than the academy's annual budget.

The literature on relative age, maturation and selection is summarised in section 1.4 with sources. The economic framework in 1.1 uses league and FIFA rules that apply to every academy in UEFA's territory and, through FIFA, to the Gulf.

1.1

The economics of an academy

Academies are financed as a cost centre and judged as an investment. Both views are right, and the rules of the game define how the return arrives.

The clearest public cost benchmark comes from England's Elite Player Performance Plan, which sets an operating budget of at least £2.5 million and a minimum of eighteen full-time staff for a Category One academy.¹³ Those are floors; leading academies spend a multiple of them. The league reports that more than £2.5 billion has been invested in youth development since 2012, and claims over £4 billion in transfer and loan fees generated by academy graduates of Premier League and EFL clubs in the same period.¹⁴ Both figures are the league's own, and both say the same thing: the money is real in both directions.

The return arrives through five channels. Two are sporting: first-team minutes that would otherwise be bought, and squad-list compliance (UEFA requires eight home-grown players in a 25-man list, four of them club-trained). Three are financial and rule-based: transfer fees for graduates, FIFA training compensation, and the solidarity mechanism. The last two are frequently under-claimed because they depend on registration records, which is a data-governance problem before it is anything else. Since November 2022 the FIFA Clearing House has processed training rewards centrally; the evidence it needs is the academy's own registration history.

Two academy business models

The CIES data on page 7 separate academies by how much of their graduates' top-league playing time happens at the training club itself. Athletic Club retains 66% and Real Sociedad 58%; Real Madrid and Paris Saint-Germain retain 13%.¹² The first model supplies the first team; the second supplies the market. Both are legitimate, and they call for different intelligence: pathway, loan and contract decisions in the first, valuation and timing in the second. An academy that has not decided which model it runs cannot decide what to measure.

FIFA TRAINING COMPENSATION, UEFA CLUBS (PER SEASON OF TRAINING)¹⁵

Category I	€90,000
Category II	€60,000
Category III	€30,000
Category IV	€10,000

Seasons of the 12th to 15th birthday are always valued at the Category IV rate. Payable on first professional registration and on international transfers until the season of the 23rd birthday, at the new club's category.

SOLIDARITY MECHANISM¹⁶

Share of any transfer fee	5%
Seasons of 12th–15th birthday	0.25% each
Seasons of 16th–23rd birthday	0.5% each

Distributed by the buying club to every club that registered the player in those seasons; triggered on every subsequent transfer, not only the first.

ILLUSTRATION, NOT A FORECAST

An academy with 200 registered players and a €3 million budget spends about €15,000 per player-season. A single graduate later transferred for €10 million returns €500,000 in solidarity alone to the clubs that trained him, before any sell-on clause. One decision made better at fourteen can fund thirty player-seasons.

£2.5m

minimum operating budget, Category One academy, England (plus eighteen full-time staff)¹³

8 / 25

home-grown players required in a UEFA competition squad list, four of them trained by the club itself

62%

of La Liga minutes played by locally trained players; 42% in the Premier League, 39% in Serie A¹⁷

>£4bn

league-reported transfer and loan fees generated by English academy graduates since 2012¹⁴

1.2

What output looks like: benchmarks from twenty seasons

The CIES Football Observatory traced every player who appeared in Europe’s five major leagues between 2005/06 and January 2025 back to the club that trained him. The numbers are a corrective to almost every marketing claim about talent production.

TRAINING CLUB	PLAYERS	OWN-CLUB MINUTES	MODEL
Real Madrid	166	13.4%	Market
FC Barcelona	156	29.0%	Mixed
Paris Saint-Germain	111	13.0%	Market
Olympique Lyonnais	103	26.4%	Mixed
Manchester United	103	26.2%	Mixed
Stade Rennais	94	26.2%	Mixed
Atalanta	94	19.8%	Market
Athletic Club	89	66.3%	First team
Valencia	87	25.0%	Mixed
Toulouse	87	35.1%	Mixed
Bayern München	80	32.0%	Mixed
Real Sociedad	77	58.1%	First team

Training club: first team where a player spent at least three seasons between his 15th and 21st birthdays (UEFA definition). Own-club minutes: share of the graduates’ major-league minutes played for the training club itself. Outside the five leagues: Ajax 73 players, Sporting CP 64, River Plate 51, Boca Juniors 49, Benfica 45, Dinamo Zagreb 35. Source: CIES Monthly Report 99, February 2025.¹²

13,881

players appeared in the five major leagues over twenty seasons, trained by 2,424 clubs in 116 associations

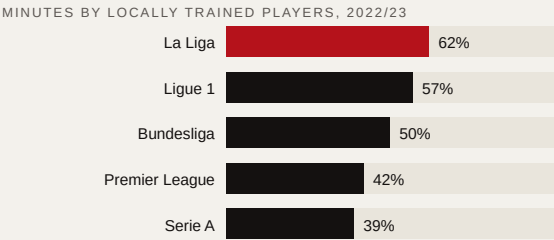
58.6%

of those players were trained outside the five countries that host the leagues

3 + 1

players trained in Saudi Arabia (two clubs) and Qatar (one club) over the same twenty seasons

The average training club that produced at least one major-league player produced fewer than six in twenty years. The distribution is extremely skewed: a few dozen clubs account for most of the output, and thousands account for one player each.



Share of domestic-league minutes played by locally trained players, 2022/23 season, five major leagues. Source: UEFA, *The European Club Footballing Landscape* (2023), cited in Smokvina (2026).¹⁷

What the benchmarks imply for AI

Any model whose target is "will this player reach a major league" is trying to detect an event that occurs, for a typical academy, a handful of times per decade. The signal cannot be recovered from a single institution's data, and pooled data across institutions raises the very legal and governance questions that Part IV addresses. The sensible targets are intermediate and observable within a season or two: minutes by maturity band, injury burden, progression between phases, retention of late developers, time to first professional contract, and the outcome of loans.

The Gulf figures are not a verdict on Gulf academies, several of which are less than a decade old. They are a reminder that screening 1.7 million pupils and producing professionals are different problems, and that the second is solved in the development years, not at intake.

1.3

The twelve decisions that determine academy outcomes

Every item below is decided in every academy every year, and almost none is recorded in a way that lets the institution learn from it. The "AI upside" column rates how much a well-designed intervention can improve the decision on current evidence.

#	DECISION	WHEN	INFORMATION TYPICALLY USED	COST OF A WRONG CALL	AI UPSIDE	FIRST MOVE
1	Intake at the foundation phase	U8–U11, annual trial days	Coach opinion, trial-match impression; no maturity data	Low per case, high in aggregate: the pool is skewed towards relatively older boys from day one	LOW for selection MED for audit	Report birth-quarter distribution of every intake cohort
2	Annual retain / release	U12–U16, end of season	Coach reviews, physical tests, minutes played	The largest hidden cost in the system: late developers removed; compensation exposure if they succeed elsewhere	MED	Maturity status recorded for every release; second-review protocol
3	Recruitment from other clubs	U12–U16, windows	Scouting reports, video, tariff tables	Compensation paid for a player who does not progress; reputational cost with local clubs	MED	Structured report template; searchable archive
4	Position and role assignment	Continuous	Coach judgement	Late repositioning wastes development years	MED	Event data from video to test role hypotheses
5	Playing up, playing down, bio-banding	Continuous	Height, "readiness", availability	Early maturers under-challenged; late maturers overwhelmed and injured	HIGH	Predicted-adult-height estimates every quarter
6	Training load and return to play	Weekly	GPS where used, wellness forms, medical opinion	Growth-related injury burden; lost development time	HIGH	Individual baselines; growth-rate flags
7	Scholarship / apprenticeship offer	Age 16	Reviews, school reports, coach consensus	Two or three years of full-time cost on a player who will not progress; or a competitor's gain	MED	Decision ledger entry with options considered
8	First professional contract	Age 17–18	Coach consensus, agent pressure, market rumour	Wages and squad place committed; asset lost for nothing if not offered	MED	Portfolio view: cohort, positions, pathway capacity
9	Loan placement	Age 18–21, windows	Personal networks, availability	A season without minutes; development stalls at the most expensive age	MED	Fit criteria and minutes tracking for every loan
10	Sale, release or retention at 19–21	Windows	Market interest, first-team need	Undervalued sale, or a contract that expires with no sell-on protection	MED	Valuation range and clause design before negotiations
11	Coach assignment and development	Annual	Availability, licence level	Methodology drift; the same coach bias applied to five cohorts	LOW–MED	Session and match footage reviewed against the methodology
12	Family communication and welfare	Continuous	Informal, inconsistent	Disputes, complaints, safeguarding failures, early exits	MED	Consistent written communication, drafted with assistance, signed by a person

Decisions 7 to 10 carry most of the financial variance; decisions 1, 2 and 5 carry most of the bias. The cheapest interventions (measuring maturity, recording decisions, auditing intake) therefore protect the most expensive outcomes. Upside ratings reflect published evidence as at September 2026 and the author's judgement: High, a documented and repeatable improvement using available data; Medium, a plausible gain that depends on the academy's own record-keeping; Low, evidence does not support deployment for that decision.

1.4

Why prediction is the wrong first target

Talent prediction is the product every academy is offered first. Four properties of the problem make it the use case least likely to work, and the one most likely to do harm if it appears to.

Base rates

Aspire's Football Dreams programme screened 3.5 million thirteen-year-olds across seventeen countries between 2007 and 2014 and awarded eighteen to twenty scholarships a year.¹¹ Within a professional academy the funnel is narrower than it looks: a typical institution registers around two hundred players and produces a professional every year or two. A classifier trained to find events that rare will be dominated by noise, and its apparent accuracy in testing will not survive contact with a new cohort.

Sample size

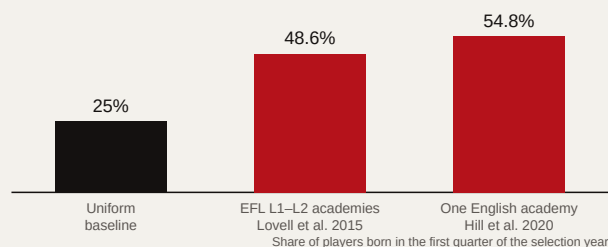
Published machine-learning studies of academy development have used samples of 98 players for development ratings and 18 players for the contract decision, with 53 candidate variables.¹⁸ The authors were appropriately cautious; vendors quoting such work are not. With fewer observations than variables, any model can be fitted to anything.

Circularity

The only outcome labels an academy possesses are its own past decisions: who was retained, who was given minutes, who was offered a contract. A model trained on them learns the coaches' preferences, including the preference for relatively older and earlier-maturing boys. Once deployed, its scores influence the same decisions, so the prediction helps to cause the outcome it claims to foresee.

Delay

The true outcome is known five to twelve years after the prediction. No model can be validated on the horizon that matters within the tenure of the people who bought it.



Share of academy players born in the first quarter of the selection year, against a uniform baseline of 25%. Sources: Hill et al. (2020), one English professional academy, U9–U16, 566 observations over eight years; Lovell et al. (2015), English League One and Two academies, U9–U18.^{2–3}

The bias the data would learn

In one English academy, 54.8% of players were born in the first quarter and, on the least conservative maturity criterion, none of the U15 and U16 players was late-maturing.² Across 1,011 players in twelve Scottish academies, a significant bias towards early maturers emerges at U12 and grows to a large effect by U18.⁴ The reverse pattern appears at the exit: in one cohort followed to adulthood, 76.2% of players born in the final quarter went on to a professional contract, against 46.6% of those born in the first.¹⁹ The relatively young who survive the system are, on average, the better players. The system removes most of them before anyone finds out.

A potential score trained on academy history is a bias with a confidence interval. The correct first use of the data is to measure the bias, change the decision process, and record what was decided. Prediction can wait until there is something honest to predict.

PART II

II Where AI changes outcomes: the use-case map

Six domains cover everything an academy is realistically offered. Each is rated on the strength of the evidence, the data it needs, an indicative annual cost band, its regulatory exposure and a verdict. The following pages take each in turn.

DOMAIN	EVIDENCE BASE	DATA REQUIRED	INDICATIVE ANNUAL COST	REGULATORY EXPOSURE	VERDICT	FIRST MOVE
2.1 Selection-bias auditing	STRONG	Registration history, dates of birth, heights, parental heights	Analyst time only; €0–15k if outsourced	LOW	DO NOW	Birth-quarter and maturity distribution for every age group, this season
2.2 Growth, load and injury	STRONG (growth) MODERATE (load models)	Quarterly anthropometrics, exposure, injury log, wellness; GPS from U14	€10–80k depending on wearables and platform	MEDIUM (health data)	DO NOW	Growth-measurement calendar; individual baselines
2.3 Video and event capture	MODERATE	Cameras per pitch, storage, analyst workflow	€2–6k per camera-year; €30–150k for a full site	MEDIUM (images of minors)	DO WITH CARE	One pitch, three coaches, a written review workflow, one season
2.4 Institutional memory and generative AI	MODERATE (documented deployments, first-team level)	The academy's own reports, plans and notes, digitised and access-controlled	€15–60k for an enterprise deployment; €0–5k for a bounded pilot	HIGH if misconfigured; Low if enterprise-grade	DO WITH CARE	Retrieval over three seasons of player reviews for one age group
2.5 Recruitment and external scouting	MODERATE (adult data); WEAK (youth prediction)	Licensed event and video data; structured internal reports	€10–100k for data licences at youth level	HIGH (minors, FIFA rules)	DO WITH CARE	Structured report template before any data licence
2.6 Pathway and squad economics	MODERATE	Decision ledger, contracts, loan minutes, market values	Analyst time; €0–20k	LOW	DO NOW once the ledger exists	Cohort conversion rates by phase, five seasons back
Talent prediction (ranking children by future value)	WEAK	Historical selections (circular)	Whatever the vendor asks	HIGH	WAIT	None. See 1.4 and 2.7

Cost bands are the author's indicative estimates for a professional-club academy of 150–250 players, in euros, excluding staff already employed; they are not benchmarks. Regulatory exposure refers to the EU AI Act and data-protection law as summarised in Part IV; it is a design consideration, not a legal classification.

The order of the domains is deliberate. The first two use data the academy already holds or can collect with a tape measure and a set of scales. The third and fourth create new data and new obligations. The fifth and sixth depend on the record-keeping described in Part III. Prediction appears last because it is where the money is asked for first.

2.1

Selection-bias auditing: start with the mirror

Before an academy buys anything that looks at players, it should look at itself. The audit is statistics rather than machine learning, which is exactly why it works: the method is transparent, the data exist, and the result changes decisions in the same season.

What the audit measures

- **Relative age.** Birth-quarter distribution of every age group and every intake cohort, against the population baseline of the catchment. English academies run at roughly half of players born in the first quarter.²⁻³
- **Maturation.** Each player's biological maturity, estimated non-invasively from current height, weight, age and parental heights (Khamis-Roche gives percentage of predicted adult height; Mirwald gives years from peak height velocity). Players are classified early, on time or late.
- **Where the bias enters.** Retention and release decisions, match minutes and selection for representative squads, cross-tabulated by birth quarter and maturity band, for at least five seasons.
- **What it costs.** The share of late developers still present at U15–U16; the share of released players who signed elsewhere; compensation received or paid as a result.

What it produces

A two-page board note with four charts and the decision points where the effect is largest. It is not a judgement on individual coaches: the effect appears in every academy studied, including the best funded.

Where software helps, and where it does not

A spreadsheet can do the first audit. A platform earns its place when measurements arrive monthly for two hundred players, estimates must be recalculated automatically, and coaches need a maturity band beside a name at selection time. Anything sold as "AI talent identification" that does not first report the academy's own selection bias is not worth a meeting.

01

Assemble

Eight to ten seasons of registrations: identifier, date of birth, entry and exit dates, exit reason, age group, minutes where available. Two to three weeks of one analyst.

02

Measure

Height, sitting height and weight for every current player, plus parental heights by questionnaire. Quarterly thereafter; monthly around the expected growth spurt.

03

Cross-tabulate

Retention, release, minutes and selection by birth quarter and by maturity band. Report effect sizes, not only percentages.

04

Intervene

Bio-banded fixtures and training groups; maturity-adjusted physical benchmarks; a late-developer watch list reviewed by someone other than the age-group coach; release decisions deferred one cycle where maturity is late.

05

Record

Every retain or release decision enters the ledger (3.2) with maturity status and birth quarter attached, so next year's audit reads the decisions, not the outcomes.

06

Repeat

Annually, at the same point in the season. The first audit describes the problem; the second shows whether the interventions moved it.

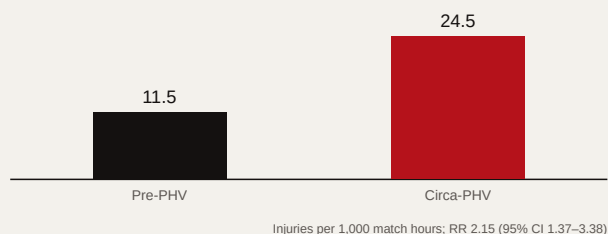
WHY THIS IS ALSO A GOVERNANCE MOVE

Recording maturity status at every release decision is the cheapest protection against the two failure modes that matter: a late developer succeeding elsewhere, and a family's complaint that a child was removed for being small. Under the AI Act's high-risk regime (Part IV), documented human oversight of selection decisions is required; here it is the product.

2.2

Growth, load and injury

The adolescent growth spurt is the most predictable risk event in an academy's calendar and the least systematically managed. Software adds value here by watching each player against himself, not by producing a risk score.



Injury incidence per 1,000 hours by maturity period, non-contact and overuse injuries in competitive matches, one English professional academy, 76 players over two seasons. Source: Johnson et al. (2020).⁶

The benchmarks

In a Dutch top-flight academy followed for up to three seasons, injury incidence across U12–U19 averaged 8.3 per 1,000 hours and peak height velocity arrived at a mean age of 14.4, with a range of 12.8 to 16.5.⁵ Around the growth spurt, incidence in the English cohort above more than doubled.⁶ Players growing faster than 7.2 cm a year carry the highest growth-related injury burden, and the risk rises roughly linearly with growth rate.⁷ Across the literature, academy incidence ranges from 2.0 to 19.4 per 1,000 hours, higher than the professional game.⁵

The spread in timing is the operational point. Two players in the same U14 group can be three years apart biologically. Training them on the same load because they share a birth year is a policy, and the injury log is where the policy shows.

What to put in place

- **A measurement calendar.** Height, sitting height and weight quarterly from U11; monthly for players within a year of predicted peak height velocity. Parental heights collected once. Estimates recalculated automatically.
- **Exposure and injury logging** by the medical department to a common standard, with growth-related diagnoses coded separately.
- **Individual baselines.** Each player's load, wellness and growth compared with his own history rather than with the squad. This is where a platform earns its cost: the arithmetic is simple, the volume is not.
- **Flags, not verdicts.** A fast-growth flag, a load-spike flag and a wellness-drop flag land with the physiotherapist and the coach, who decide. The log records what they did.
- **Education** of coaches and families on what the growth spurt does to coordination, bone and tendon, and why load is reduced for the player who has just grown eight centimetres.

Two cautions

Ratios are not oracles. The acute-to-chronic workload ratio, still embedded in many products, has been criticised in the sports-science literature for methodological weaknesses and inconsistent predictive value.²³ Use load metrics as description, not prophecy.

"Injury prediction" is a claim, not a feature. Any vendor asserting it should show validation on youth cohorts, with false-positive rates, and accept that the academy's medical staff remain accountable. Health data are a special category under data-protection law; a wearable at U10 needs a reason.

VERDICT

Do now. Growth monitoring costs a stadiometer and discipline. The platform decision can follow once the measurement habit exists.

2.3

Video and event capture

Automated cameras have made full-match footage of every academy fixture affordable. What they have not made affordable is the coaching time to use it. Buy the workflow before the hardware.

What the current generation delivers

Single-unit panoramic cameras record the whole pitch without an operator, follow play automatically and produce clips of goals, set pieces and user-defined moments. Fixed installations cover a training ground permanently; portable units travel to away fixtures. Vendor-reported pricing in 2025–26 ranges from roughly \$1,200–1,500 for a portable unit plus a required analysis subscription, to about \$950 plus \$70–170 a month for a comparable product, to installed platforms from around \$3,100 a year per site.²⁰ A ten-pitch training ground with away coverage lands in the tens of thousands of euros a year once storage and subscriptions are counted.

FC Barcelona's innovation unit co-developed a portable automated camera with Pixellot for use across its 44 Barça Academies, with instant tagging, heat maps and phase breakdowns; the stated purpose was to assess how the club's methodology is applied, not to grade children.²¹ That framing is the right one.

What it does not deliver

- Tracking-grade positional data. Youth formats (7v7, 9v9, small pitches, no shirt numbers, changing kits) defeat most automated identification; treat any "player tracking" claim at academy level as unverified until tested on your own matches.
- Event data of professional quality without human correction. Automated tagging accuracy varies by system and by camera position; validate on a sample before relying on statistics.
- Coaching. Footage that no coach reviews with a player is an expense.

The pilot that answers the question

01

One pitch, three coaches, one age group

Choose the phase where individual feedback matters most (U14–U16). Fixed camera on the match pitch, portable for away games.

02

A written review routine

Ten minutes per player per fortnight, two clips chosen by the coach against the individual plan, one chosen by the player. Attendance and time logged.

03

A measured season

Compare review frequency, player-reported usefulness and coach time against the age group without cameras. Decide on expansion from the numbers, not the demonstration.

Consent, images and safeguarding

Recording minors is lawful with an appropriate basis and clear information to families, but retention, access and any external sharing need rules before the first fixture is filmed. Footage should be visible to named staff only, never posted publicly without specific consent, and deleted on a schedule tied to the player's registration. Opposition players appear in every recording; the club's safeguarding lead should sign the policy. Where a system generates synthetic or edited output, the AI Act's transparency rules on AI-generated content apply from August 2026, and from December 2026 for systems already on the market.⁹

VERDICT

Do with care. High adoption, moderate evidence, real cost, manageable risk. The pilot above costs less than a mid-table full-back's monthly wage and settles the question.

2.4

Institutional memory and generative AI

An academy of twenty years' standing holds thousands of written player reviews, plans and reports that no current member of staff has read. Large language models are good at exactly one thing an academy needs: reading everything, and answering from it with references.

The pattern that works

In 2024 Sevilla FC deployed Scout Advisor, built on IBM's watsonx platform and, in its current version, on Meta's Llama 3.1 model, to search and summarise a database of more than 200,000 of the club's own scouting reports in natural language.⁸ The design matters more than the brand: the model does not invent judgements, it retrieves the club's judgements and presents them with their source. Applied to an academy, the same architecture answers questions such as "what did every coach write about this player's decision-making under pressure since U13" in seconds, with the passages attached.

Six academy uses, in order of value

- 01 Synthesis of a player's full review history before a retention, scholarship or contract meeting, with citations to the original documents.
- 02 First drafts of individual development plans from coach notes, in the academy's own template and vocabulary, edited and signed by the coach.
- 03 Normalisation of scouting and match reports into a structured format, so that ten scouts' prose becomes comparable.
- 04 Family communication: consistent letters, translated for multilingual families, reviewed by a person before sending. In Gulf academies with expatriate staff and Arabic-, English-, French- and Portuguese-speaking households, this alone justifies the tool.
- 05 Session-plan assistance for coaches, constrained to the club's methodology documents.
- 06 Minutes, action lists and ledger entries from decision meetings, transcribed and structured for review.

The guardrails that make it lawful

- **No personal data of minors in consumer tools.** Free chat products are not a permitted home for a child's medical note, review or name. Enterprise deployments with contractual no-training and no-retention terms, hosted in an approved region, are.
- **Role-based access** mirroring the paper world: medical notes stay with medical staff; the model cannot read what the user could not.
- **Provenance on every answer.** If the system cannot show the passage, the answer is not used.
- **Human signature.** Every plan, letter and report leaves the building under a named person. The model drafts; it does not decide and does not send.
- **An evaluation set.** Fifty questions with known answers, run at every model update, so that quality drift is detected by the academy and not by a parent.
- **Logged prompts and outputs**, retained for as long as the underlying records.

What to expect, honestly

Documented deployments in football are at first-team level and their results are self-reported. The author's expectation, stated as such, is that the time to prepare a decision meeting falls by well over half and that the quality of written plans becomes consistent across coaches. The larger effect is cultural: when every past opinion is retrievable, opinions get written more carefully.

VERDICT

Do with care. Start with retrieval over three seasons of reviews for one age group, measured against an evaluation set, before any drafting use reaches a family.

2.5

Recruitment and external scouting

Data and video have transformed adult recruitment. At youth level the same tools meet smaller pitches, thinner data, stricter rules and a moving target. The right investment is in how the academy records what its own scouts see.

What transfers from the adult market

Licensed event data and video platforms now cover many youth competitions, and marketplace tools list availability and loan interest. For players of seventeen and older, the adult playbook broadly applies: structured requirements, data-led longlists, video verification, live confirmation. The models that estimate adult transfer values are of limited use below that age, because the variance in maturation swamps the signal in performance statistics.

What does not

- **"Objective" youth rankings.** Performance data at U13–U16 measures the current body as much as the future player. A ranking that ignores maturity status is a ranking of birth dates.
- **Open-trial applications.** App-based platforms that let players upload footage or complete standardised tests extend reach at low cost; their predictive claims are the vendors' own. Use them to widen the funnel, not to narrow it.
- **Cross-border ambition.** FIFA's rules on the international transfer and first registration of minors permit it only in defined exceptions, and academy-to-academy moves within a country carry fixed compensation tariffs in several systems. A data tool that surfaces a twelve-year-old abroad surfaces a problem, not a target.

Where AI genuinely helps

Inside the academy's own reports. A structured template (context, maturity band, role, four to six graded behaviours, free-text judgement, recommendation) turns the scouting department's output into a dataset that retrieval and comparison can work on. That archive, not a licence, is the asset that compounds.

AGE BAND	SENSIBLE USE OF EXTERNAL DATA AND TOOLS	NOT SENSIBLE
U9–U12	Local network, coach reports, birth-quarter awareness in trial design	Any performance database; any ranking; wearables
U13–U16	Video verification, structured reports with maturity band, opposition analysis to find players the pool missed	Value models; cross-border targeting; social-media profiling
U17–U19	Event data on youth competitions, marketplace tools for loans, structured comparison against squad needs	Sole reliance on statistics; unvalidated "potential" scores
U20–U23	Adult recruitment toolkit, valuation ranges, contract-clause design	Ignoring the academy's own five-year record on the player

Every academy already runs the world's most expensive scouting experiment: it watches two hundred players for ten years and writes down almost nothing it can search. Fix that before licensing anyone else's data.

VERDICT

Do with care. Structured internal reporting first; licensed data for U17 and above; nothing that ranks children below that age by statistics alone.

Pathway and squad economics

Owners ask what the academy is worth. Academy directors answer with anecdotes. A decision ledger and five seasons of records allow a different answer: a pipeline with conversion rates, capacity constraints and a value at risk in every phase.

The model an owner understands

Treat the academy as a funnel with observable stages: foundation intake; entry to the youth development phase; scholarship or equivalent at sixteen; first professional contract; first-team debut or sale. For each transition, record the number of players, the conversion rate, the age at which the decision was made and the cost of the phase. Five seasons of such records tell an owner more than any presentation: where the academy loses players, at what age, and what each stage costs per player who eventually converts.

Layer three more things on top. The pathway capacity: how many first-team minutes are realistically available to graduates in each position over the next three seasons, which determines whether a contract offer is a development decision or a stockpile. The loan record: minutes obtained, level of competition, outcome on return. And the rule-based income: solidarity and training compensation received, sell-on clauses in force, and the registration continuity that supports every claim.

Where analytics helps

- Cohort analysis: conversion by intake year, by birth quarter, by maturity band, by coach.
- Scenario ranges for contract decisions: what the squad looks like if three of this cohort are retained and two are sold, against pathway capacity.
- Loan fit: level, style and minutes available, tracked against the outcome on return, so the next placement is chosen from evidence.
- Valuation ranges before a negotiation, from comparable transfers and the player's own record, not a single number from a website.

A WORKED EXAMPLE, WITH ITS ASSUMPTIONS SHOWN

STAGE	PLAYERS	CONVERSION	COST OF PHASE, €K
Foundation intake (U9–U11)	60	—	300
Youth development (U12–U16)	90	45% from foundation	1,500
Scholarship (U17–U18)	24	27%	900
First professional contract	8	33%	450
First-team debut or sale	2–3	25–40%	—

Illustrative figures for an academy of about 180 players and a €3.2 million budget, constructed by the author to show the structure of the analysis. Cohort sizes and rates vary widely between academies and countries and should be replaced by the institution's own record. The point is the shape: two thirds of the cost is spent on players who leave, which is the nature of development, and the question is whether they left for the right reasons.

Two questions the numbers answer

Should we offer the contract? Not "is he good", but "is there a pathway, is the alternative a loss for nothing, and what does the ledger say about how this coaching group's confidence has correlated with outcomes in the past".

Is the academy worth its budget? The honest answer combines first-team minutes replaced, rule-based income, realised sales and the cost of the alternative squad. Most academies have never assembled those four numbers on one page. The ledger makes it routine.

VERDICT

Do now, once the ledger exists. This is the analysis that turns an academy from a cost line into an asset an owner can reason about.

2.7

Do not deploy

A short list, agreed at board level and written into procurement rules. Each item is either prohibited, unsupported by evidence, or disproportionate to what an academy owes the children in its care.

SYSTEM OR PRACTICE	BASIS	REASON
Emotion recognition or facial-expression analysis of players in training, education or workplace settings	PROHIBITED	The EU AI Act bans AI systems that infer emotions of natural persons in workplace and education institutions, other than for medical or safety reasons, with effect from February 2025. Beyond the law, it is intrusive, unreliable with adolescents and corrosive of trust. ⁹
Biometric categorisation of players by sensitive attributes	PROHIBITED	Inferring race, religion or similar attributes from biometric data is banned under the same article. No academy purpose requires it.
Facial recognition to identify minors in video	DISPROPORTIONATE	Biometric processing of children for a purpose that a shirt number and a team sheet serve equally well. Special-category data under data-protection law; unnecessary intrusion.
Automated retain, release or contract decisions, or "potential scores" that function as the decision	UNLAWFUL AS DESIGNED	Decisions with legal or similarly significant effects on a person may not be solely automated without safeguards (GDPR Article 22); such systems fall into the AI Act's high-risk categories with obligations from December 2027; and the evidence base is weak (1.4). A human must decide, and must be able to explain why.
Sharing "potential" rankings or predicted values with players or families	HARMFUL	Labels attached to children change how they are coached and how they see themselves. A number on a fourteen-year-old is a prophecy with a feedback loop. Individual development plans, yes; league tables of futures, no.
Consumer chat tools used with player-identifiable data	UNLAWFUL IN MOST SETTINGS	No lawful basis for transferring a minor's medical, educational or performance data to a third-party service with unknown retention and training terms. Enterprise deployment or nothing.
Monitoring players' social media or behaviour outside the academy	DISPROPORTIONATE	Surveillance of children beyond the activity for which they are registered. Safeguarding concerns are raised through people, not scrapers.
Vendor "injury prediction" without validation on youth cohorts and without medical governance	UNSUPPORTED	Predictive claims in this area rest on contested methods; an unvalidated risk score changes medical decisions without accountability.
Wearables and GPS at the foundation phase without a defined purpose	DISPROPORTIONATE	Data collected because the device exists, not because a decision needs it. The necessity test (4.2) fails.
Predictive models trained only on the academy's own historical selections	UNSUPPORTED	Circular labels reproduce the selection biases documented in 1.4 and present them as objectivity.
Data collection with no named decision it serves	PRINCIPLE	Every field in the record must be traceable to one of the twelve decisions in 1.3. If it is not, it is liability, storage and a future breach.

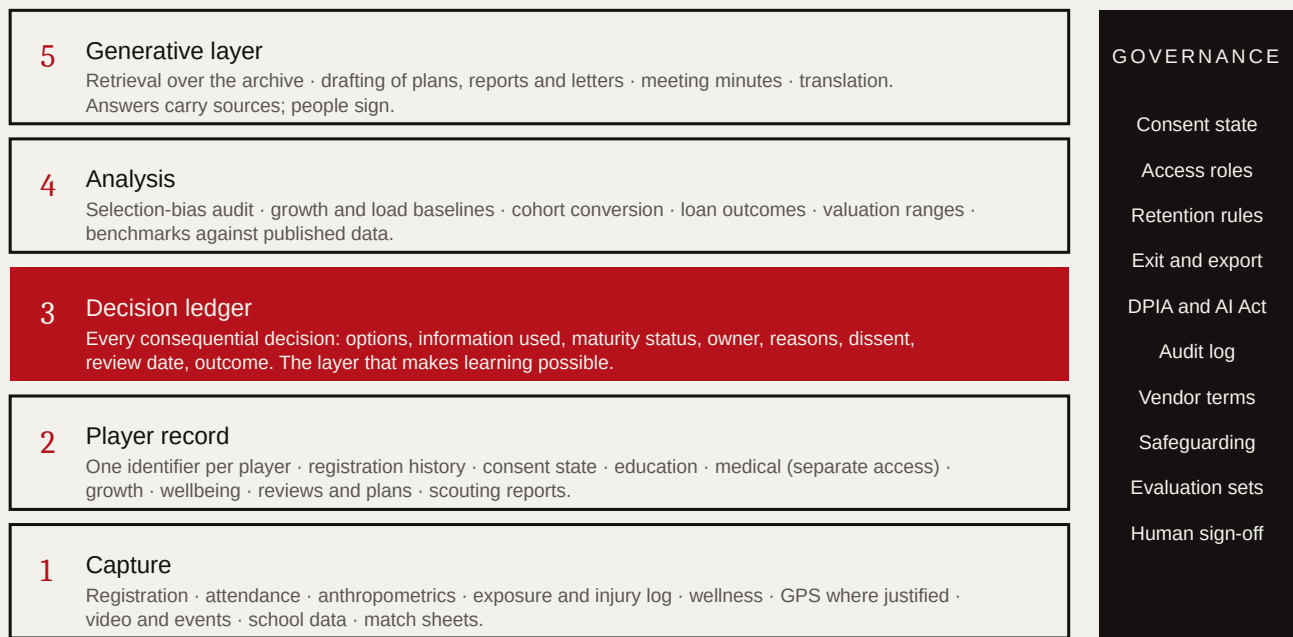
Regulatory references are summarised, not exhaustive, and are current to September 2026. Where a supplier disputes a classification, the academy's counsel, not the supplier's, decides whether the system is procured.

PART III

III The academy intelligence stack

Five layers, one discipline. The layers can be bought from different suppliers or built in a spreadsheet; the discipline cannot be bought at all. It is that every record has a source and a date, every decision has an entry, and every field serves a decision.

3.1 · FIVE LAYERS AND ONE DISCIPLINE



The academy intelligence stack. Layers 1, 2 and 3 can be run in commodity software; layers 4 and 5 are where platforms and models earn their cost. Governance applies to every layer and is owned by the academy, never by a supplier.

Six rules of the record

- 01 One identifier per player, for life, across every system and supplier.
- 02 Every record carries its source, its date and who entered it.
- 03 Consent is a state, not a signature: recorded per purpose, revisited at each registration, and honoured by every system that reads the data.
- 04 Medical data live behind their own door. Coaches see availability, not diagnosis.
- 05 When a player leaves, the academy can export his complete record in a readable format within days, and delete what it has no basis to keep.
- 06 No field without a decision. If nobody can name the decision a data point serves, it is not collected.

Build, buy or spreadsheet

Layer 1 is mostly bought (cameras, wearables, registration systems). Layer 2 is bought where a league provides it, as in England, where the Premier League commissioned a successor to its academy platform from Kitman Labs in 2023,²² or assembled from a modest database elsewhere. Layer 3 is built, because no supplier sells it and it must reflect how this academy actually decides; a disciplined spreadsheet is an acceptable first version. Layer 4 starts as analyst work and graduates to a platform when the volume justifies it. Layer 5 is bought as an enterprise service and configured, never trained, on the academy's data.

The commonest failure is to buy layer 5 or layer 4 before layer 3 exists. The result is fluent summaries of an archive that records what happened but not why, which is the one question that matters.

3.2

The decision ledger

A ledger is a record of decisions made before their outcomes are known. It is the only instrument that lets an academy learn faster than staff turnover, and it is the document a regulator, a family's lawyer or a new owner will ask for first.

What goes in

One row per consequential decision, of the twelve types in 1.3. The full field list is in Appendix A; the essentials are the decision type and date, the player identifier, the options that were considered, the option chosen, the information that was actually in the room (with links to the reviews, data and video used), the player's maturity status and birth quarter at the time, the decision owner and the participants, the reasons in two or three sentences, any dissent, a confidence level, and a date on which the decision will be reviewed against what happened.

The outcome columns are filled later: at twelve, twenty-four and sixty months. A released player who signs professionally elsewhere, a retained player who leaves at sixteen, a loan that produced no minutes: each is a data point that only exists because the decision was written down first.

Why it is the first AI project

- **Learning.** Without recorded decisions, outcome data can only be explained by the people who remember, and they have left.
- **Bias detection.** The audit in 2.1 reads the ledger, not the anecdotes, from its second year onwards.
- **Regulation.** The AI Act's high-risk regime requires documented human oversight and record-keeping for systems that support selection and contract decisions; data-protection law requires that automated processing be explainable to the person concerned. The ledger is that documentation.
- **Disputes.** When a family, an agent or a former player challenges a decision, the academy shows what it knew, what it considered and who decided.
- **Money.** Registration continuity is the evidence behind every training-compensation and solidarity claim; the ledger links decisions to registrations.
- **Memory.** A new academy director inherits a reasoning history, not a cupboard of filed reviews.

EXAMPLE ENTRY

Type	Retain / release, U14, end of season
Player	A-2031-047 · Q4 birth · late maturing (Khamis-Roche 84% of predicted adult height)
Options	Release · retain one further season · retain with bio-banded placement
Decision	Retain, bio-banded placement with U13 for competition, U14 for training
Information	Three coach reviews (linked) · minutes: 41% of available · growth 8.9 cm in twelve months · no injury · school report
Owner	Head of youth development phase
Reasons	Technical and decision-making ratings above the group median; physical ratings below. Growth spurt in progress. Release would remove a late developer on the basis of maturity.
Dissent	Age-group coach favoured release; concern about competitive readiness recorded.
Confidence	Medium
Review	End of next season; outcome fields at +12, +24, +60 months

COST AND FORMAT

A spreadsheet with locked columns and a monthly export is an acceptable first year. What matters is the habit: no consequential decision leaves the meeting without a row, and the row is written before the meeting ends. Expect two hundred to four hundred rows a season for a full academy. A database with role-based access follows in year two, when the generative layer needs to read it.

Identifiers are pseudonymous in every export. Names are resolved only inside the access-controlled record.

3.3

Data governance for minors

An academy processes more categories of sensitive data about children than almost any organisation that is not a hospital or a school. The governance is not complicated; it is simply absent in most places.

DATA CLASS	EXAMPLES	SENSITIVITY	RULES THAT FOLLOW
Identity and registration	Name, date of birth, nationality, registration history, guardians	Personal data of a minor	Lawful basis documented; guardians informed in plain language; retention tied to registration plus the period needed for compensation claims.
Health and medical	Injuries, treatment, growth and maturation estimates, screening results	Special category	Medical staff control; explicit basis; coaches see availability and load guidance only; no export to suppliers without a specific contract; no generative tool outside an enterprise deployment.
Performance and tracking	Test results, GPS, event data, ratings, reviews	Personal data; profiling risk	Purpose per field; automated profiling with significant effects requires human review; ratings visible to players in a form agreed with families.
Images and video	Match and training footage, clips, photographs	Personal data; safeguarding	Named-staff access; no public posting without specific consent; retention schedule; opposition players covered; safeguarding lead signs the policy.
Education and welfare	School reports, wellbeing questionnaires, family circumstances	Personal data; some special category	Player-care staff control; minimum fields; wellbeing responses never used for selection.
Biometric	Facial or gait templates	Special category	Not collected. See 2.7.
Decisions	The ledger (3.2)	Personal data; legal significance	Pseudonymous exports; owner-only editing; retained for the life of the player's registration plus limitation periods.

Roles that must exist

- **Data owner** for the academy (usually the academy director), accountable for the register of systems and purposes.
- **Data protection officer or adviser**, internal or external, who signs the impact assessment for any new system touching minors' data.
- **Safeguarding lead**, who co-signs anything involving images, communication with players, or access by third parties.
- **Medical lead**, who controls the health data door.
- **System owner** per platform, named, responsible for access lists, vendor terms and the evaluation set.

The impact assessment

Systematic monitoring or profiling of children triggers a data-protection impact assessment in the EU and the UK before processing begins. Treat it as a design document, not a form: it makes the academy write down which decision the system serves, who sees what, how long data are kept and what happens when a family objects.

Exit rights, in practice

Every season, players leave. Each departure tests the governance: can the academy export the complete record in a readable form, transfer what the family asks for, retain what compensation rules require, and delete the rest? A released fifteen-year-old's medical history and video should not sit in a supplier's cloud because nobody owned the deletion.

Jurisdictional notes

Digital-consent ages differ (Spain 14, the United Kingdom 13, between 13 and 16 across the rest of the EU, with 16 as the GDPR default); the UK's Children's Code adds design standards; Saudi Arabia's data-protection law has been enforced since September 2024 with its own consent and transfer rules, and the UAE and Qatar have laws of their own. Across regions, design to the strictest applicable rule.

THE ONE-LINE TEST

Could the academy director explain to a parent, in two minutes, what is held about their child, who sees it, why, and how to have it removed? If not, the governance is unfinished.

3.4

Vendor due diligence: twenty questions

Ask them in writing before the demonstration, and keep the answers. A supplier that cannot answer half of them is selling a product built for a first team, or for nobody.

Data and ownership

- 01 Who owns the data and the derived data? Can we export everything, in documented formats, at any time and at termination?
- 02 Is our data used to train or improve models for other customers? If so, is that opt-in, and what exactly is used?
- 03 Where are data hosted and processed, and which sub-processors are involved?
- 04 How are minors' data handled differently, if at all? Show the controls, not the policy.
- 05 What is deleted, and when, when a player leaves us or we leave you?

Evidence and accuracy

- 06 Which academies, not first teams, use the product, and may we speak to two of them?
- 07 Has accuracy been validated on youth football (small-sided formats, mixed maturity), and can we see the validation, including false-positive rates?
- 08 What happens when the model is updated? Are we told, and can we re-run our evaluation set before accepting the change?
- 09 For any predictive claim: on which cohort, over what horizon, against what baseline?
- 10 Can the system show the source of every output, so that a coach can explain it to a parent?

Regulation and safeguarding

- 11 Under the EU AI Act, do you consider the product high-risk for any of our intended uses, and are you the provider? What documentation will you supply to us as deployer?
- 12 Does the product infer emotions, categorise by biometrics, or identify individuals from faces? If any answer is yes, the conversation ends.
- 13 Will you support our data-protection impact assessment with a completed questionnaire and technical description?
- 14 How is access controlled and logged, and can medical data be walled off from coaching users?
- 15 What is your incident history, and how would we be notified of a breach involving our players?

Commercial

- 16 Pricing per pitch, per player, per user and per site, with three-year total cost including storage and mandatory subscriptions.
- 17 What is the exit cost, and how long does a full export take?
- 18 Which features on the roadmap are sold today, and which are demonstrated only?
- 19 What internal staff time do reference customers report to operate the product weekly?
- 20 What happens to our data and service if you are acquired or cease trading?

Score the answers, weight the first fifteen at three times the last five, and let the procurement committee see the sheet before the demonstration. Demonstrations are designed to be persuasive; questionnaires are designed to be answered.

PART IV

IV Regulation and safeguarding as design constraints

The EU AI Act is the first law to classify the uses an academy is being sold. Most academies have not noticed that it applies to them, because they see themselves as sports organisations rather than institutions of education, vocational training and employment. In the Act's terms, they are all three.

4.1 · THE EU AI ACT, MAPPED TO ACADEMY USE CASES

The timeline after the 2026 amendments

2 Feb 2025 IN FORCE	Prohibited practices apply, including emotion inference in workplace and education settings and biometric categorisation by sensitive attributes. AI-literacy duty: staff who use AI systems must be trained.
2 Aug 2025 IN FORCE	Obligations on general-purpose model providers; governance and penalties.
2 Aug 2026 IN FORCE	Transparency (Article 50): disclosure when people interact with AI systems; marking of AI-generated content.
2 Dec 2026	New prohibitions added by the Digital Omnibus; marking extends to systems already on the market.
2 Dec 2027	High-risk obligations for stand-alone Annex III systems, including education, vocational training and employment. Deferred from 2 August 2026 by the Digital Omnibus.
2 Aug 2028	High-risk obligations for AI embedded in products under existing EU safety law, such as medical devices.

Sources: Regulation (EU) 2024/1689 as amended by Regulation (EU) 2026/1744, the Digital Omnibus on AI, in force since 27 July 2026.⁹ Dates apply to EU-established or EU-serving deployers; UK and Gulf academies using EU suppliers inherit obligations through contracts.

Academy use cases, mapped

ACADEMY USE	LIKELY POSITION	WHAT FOLLOWS
Inferring players' emotional state from faces, voice or posture in training or classroom settings	PROHIBITED Art. 5(1)(f)	Do not procure. Medical and safety exceptions are narrow.
Categorising players by biometrics into sensitive groups	PROHIBITED Art. 5(1)(g)	Do not procure.
AI supporting admission to, or selection within, the academy as an education or vocational-training institution	HIGH-RISK Annex III, education	From 2 Dec 2027: risk management, data governance, logging, human oversight, transparency to affected persons; deployer duties including training and monitoring.
AI evaluating development or "learning outcomes" and steering the programme	HIGH-RISK Annex III, education	As above. AI-assisted individual development plans sit close to this line.
AI informing contract offers, renewals, terminations or performance evaluation of contracted players and staff	HIGH-RISK Annex III, employment	As above. Scholars and professionals are workers; the ledger is the oversight record.
Load, growth and injury tools that meet the definition of a medical device	HIGH-RISK Annex I route	Supplier conformity under medical-device rules; academy verifies status.
Automated cameras, tagging, video search, retrieval and drafting assistants	MINIMAL / LIMITED	Transparency where people interact with the system; marking of generated content; data-protection law governs the rest.
Any staff use of AI tools	ARTICLE 4	AI-literacy obligation since February 2025: documented training for the people who use the systems.

"Likely position" is the author's reading of the Act's categories against typical academy uses, not legal advice; classification of a specific system depends on its purpose and design. The academy is normally the deployer and the supplier the provider; contracts should say which.

4.2

Data protection, safeguarding and the four tests

Two bodies of rules already bind every academy before the AI Act adds a third. Data-protection law governs what may be collected and decided about a child; safeguarding frameworks govern how adults with access to children must behave. AI systems sit inside both.

Data protection, in five points

- 01 **Children are a protected group.** Consent by or for a minor is subject to an age threshold (14 in Spain, 13 in the UK, 16 by default in the EU) and to plain-language information for families.
- 02 **Health and biometric data are special categories.** Growth estimates, injury records and any biometric template need an explicit basis and stricter access.
- 03 **Solely automated decisions with significant effects are restricted** (GDPR Article 22).²⁵ A model may inform a release or contract decision; it may not make it, and the person concerned may demand human intervention and an explanation.
- 04 **Systematic monitoring or profiling of children requires an impact assessment** before processing (Article 35), and documented purpose, minimisation and retention.
- 05 **Portability and erasure are real rights.** The exit process in 3.3 exists because families can ask, and increasingly do.

Safeguarding

UEFA's club-licensing framework requires child and youth protection and welfare policies; associations and leagues add their own, and FIFA's Guardians programme sets a common reference.²⁴ The AI-relevant consequences are practical: who may view footage of minors; how AI-assisted communication with players is supervised; how wellbeing answers are kept away from selection; and how a system's outputs are explained to a child. The safeguarding lead sits on the procurement committee for any system that sees, hears or writes to players.

Gulf specifics

Saudi Arabia's Personal Data Protection Law, enforced since September 2024, requires a lawful basis, breach notification and controls on cross-border transfer; the UAE and Qatar follow comparable principles. Gulf academies using European suppliers, and European academies with Gulf partners, should design to the stricter rule and document the transfer mechanism before data move.

FOUR TESTS BEFORE ANY SYSTEM TOUCHES A PLAYER

Necessity

Which of the twelve decisions does this improve, and what would we do without it? If the answer is "it is interesting", stop.

Explainability

Can the coach or director who uses the output explain it to a fifteen-year-old and his parents in plain words, with the evidence? If not, the system decides and the human signs, which is the arrangement the law forbids.

Reversibility

Can a wrong output be caught and undone before it changes a child's pathway? Human review points, second opinions on releases, and the ledger's dissent column are the mechanisms.

Proportionality

Is the intrusion proportionate to the benefit for the player, not for the club? A wearable at nine, a camera in a classroom, a model of a face: each fails unless there is a child-centred reason.

THE GOVERNANCE DIVIDEND

Every requirement on this page is met by the same three instruments: the decision ledger (3.2), the data-class rules (3.3) and the vendor questionnaire (3.4). An academy that builds them for its own reasons is compliant as a by-product, and is the only kind that can deploy AI at scale when the high-risk regime applies in December 2027.

PART V

V Maturity, benchmarks and budgets

Five levels describe where an academy stands. Most professional-club academies in Europe sit at level 1 or 2, a handful at 3, and the author is not aware of any that would honestly claim level 4. The self-assessment takes ten minutes and is more useful done by three people separately.

5.1 · THE FIVE-LEVEL MATURITY MODEL AND SELF-ASSESSMENT

LEVEL	NAME	WHAT IS TRUE AT THIS LEVEL	TYPICAL FAILURE MODE
0	Paper	Reviews in documents and heads; registration in the federation system only; no shared record; growth not measured.	Institutional memory leaves with each coach.
1	Recorded	Central record with attendance, basic medical and education; some video; GPS in older groups; reviews stored, not searchable.	Data collected, never consulted at the moment of decision.
2	Measured	Quarterly growth and maturity estimates; exposure and injury log to a standard; event data from video; one bias audit completed; consent and retention rules written.	Analysis produced for presentations rather than for decisions.
3	Decision-audited	Ledger live for all twelve decision types; annual audit reads the ledger; outcomes filled at 12 and 24 months; impact assessment done; vendor questionnaire in use; AI-literacy training delivered.	Ledger kept by one person; decays when they leave.
4	Learning system	Retrieval and drafting over the archive with provenance; models validated on the academy's own cohorts; decisions reviewed against outcomes in a standing meeting; pathway economics reported to the board each season; ready for the high-risk regime.	Complacency: the system is trusted more than it has earned.

Self-assessment: twelve questions, scored 0 (no), 1 (partly), 2 (mostly), 3 (yes, and evidenced)

01 Can you produce, within a day, the birth-quarter and maturity-band distribution of every age group? ☐ 0 ☐ 1 ☐ 2 ☐ 3

02 Is height, sitting height and weight measured at least quarterly from U11, with predicted adult height estimated? ☐ 0 ☐ 1 ☐ 2 ☐ 3

03 Is every retain, release, scholarship and contract decision written down with options, reasons, owner and maturity status? ☐ 0 ☐ 1 ☐ 2 ☐ 3

04 Are decisions reviewed against outcomes at 12 and 24 months in a standing meeting? ☐ 0 ☐ 1 ☐ 2 ☐ 3

05 Do you know what share of players released in the last five seasons signed professionally elsewhere? ☐ 0 ☐ 1 ☐ 2 ☐ 3

06 Is there one identifier per player across every system and supplier? ☐ 0 ☐ 1 ☐ 2 ☐ 3

07 Can medical data be seen only by medical staff, in every system that holds them? ☐ 0 ☐ 1 ☐ 2 ☐ 3

08 Can you export a departing player's complete record within a week and delete what you have no basis to keep? ☐ 0 ☐ 1 ☐ 2 ☐ 3

09 Has an impact assessment been completed for every system that monitors or profiles players? ☐ 0 ☐ 1 ☐ 2 ☐ 3

10 Is there a written "do not deploy" list approved by the board, and a vendor questionnaire in procurement? ☐ 0 ☐ 1 ☐ 2 ☐ 3

11 Have staff who use AI tools received documented training, and is any use of consumer chat tools with player data prohibited and monitored? ☐ 0 ☐ 1 ☐ 2 ☐ 3

12 Can the board see, once a season, conversion by phase, injury burden, rule-based income and first-team minutes from graduates on one page? ☐ 0 ☐ 1 ☐ 2 ☐ 3

0–9

Level 0–1. Start with 2.1, 2.2 and the ledger. Buy nothing yet.

10–18

Level 2. Ledger and governance before any generative or predictive tool.

19–27

Level 3. Ready for a bounded generative pilot and a measured video expansion.

28–36

Level 4 within reach. Validate models on your own cohorts; prepare for December 2027.

5.2

Budget envelopes and the indicators that matter

Three academy tiers, three envelopes. The figures are the author's indicative estimates of what a sensible programme costs over and above existing staff; they are not benchmarks. An academy spending above its band should be able to name the decision the extra money improves.

TIER	PROFILE	YEAR ONE	STEADY STATE	WHAT THE MONEY BUYS
A · Elite	Category One equivalent; budget above €5m; 200–250 players; full-time analysts already in post	€150–350k	€200–400k	Growth and load platform across all phases; cameras on every pitch with away coverage; enterprise generative deployment over the archive; database-backed ledger; external audit of bias and governance; one added data role.
B · Established	Professional-club academy; budget €1.5–5m; 150–200 players; one analyst or shared with first team	€40–120k	€60–150k	Growth monitoring and injury logging platform; cameras for two or three pitches plus a portable unit; bounded generative pilot; spreadsheet-then-database ledger; annual audit by the analyst.
C · Developing	Smaller club, independent or federation academy; budget below €1.5m; under 150 players; no analyst	€5–25k	€10–35k	Stadiometer, scales and a measurement calendar; one portable camera; spreadsheet ledger and audit run by a part-time analyst or a contracted specialist; enterprise licence for drafting and translation only.

Indicators, in the order a board should read them

FAMILY	INDICATOR	REPORTED
Decisions	Share of consequential decisions with a ledger entry; share of release decisions with maturity status recorded; median days from decision to outcome review	Quarterly
Bias	First-quarter share by age group against catchment baseline; late-maturer share at U13–U16; minutes by maturity band; released players signing elsewhere	Annual audit
Health	Injuries per 1,000 hours by phase; growth-related injury burden (days lost per 1,000 hours); share of players measured on schedule	Quarterly
Output	Conversion by phase and cohort; debutants and first-team minutes; loan minutes and outcomes; sales, sell-ons, solidarity and training compensation received	Seasonal
Adoption	Coaches using video review weekly; time to prepare a decision meeting; evaluation-set score of the generative system at each update	Quarterly

Reading the bias indicators

The published range for first-quarter share in English academies is roughly 49–55%; uniform births would give 25%.^{2–3} An academy that moves from 52% to 45% over three intake cycles has changed its trial design, not its luck. The late-maturer share is more telling: the Scottish data show the bias emerging at U12, so a U14 group with a fair share of late developers is doing something most academies do not.⁴

Reading the health indicators

Published academy incidence spans 2.0–19.4 injuries per 1,000 hours, with about 8 as a central figure for U12–U19 and roughly double during the growth spurt.^{5–6} A cohort whose own log shows no growth-spurt peak is either measuring maturity poorly or not logging injuries fully; both are findings.

THE ONE NUMBER AN OWNER SHOULD ASK FOR

Cost per converted player by phase, five seasons rolling, beside first-team minutes replaced and rule-based income received. If the academy cannot produce it, the first budget line is the ledger.

PART VI

VI

The first ninety days

Nothing in this plan requires a purchase. It requires an owner, an analyst for part of the week, the medical department's cooperation and one board decision. At the end, the academy knows what it holds, what it decides, where its bias is, and what it will refuse to buy.

Weeks 1–2

Inventory and ownership

Name the owner. List every system that holds player data, its supplier, its purpose and who can see it. List the twelve decisions as the academy actually makes them: who is in the room, what is on the table. Draft the "do not deploy" list for board approval. Map existing tools against the table in 4.1.

Weeks 3–6

Measure and record

Run the selection-bias audit on eight to ten seasons of registrations. Start the growth-measurement calendar and collect parental heights. Open the decision ledger in a spreadsheet and enter every decision from the week it opens. Begin the impact assessment for existing monitoring systems. Train the staff who use any AI tool.

Weeks 7–12

Pilot and report

Choose one generative use case with a named workflow owner and an evaluation set; run it on one age group in an enterprise deployment. Issue the vendor questionnaire to any supplier under consideration. Present the board note: audit results, ledger status, governance gaps, the "do not deploy" list, and a twelve-month plan with a budget in the right envelope.

Months four to twelve

- **Quarter two.** Second growth measurement; bio-banded fixtures trialled in one phase; video pilot on one pitch with a written review routine; ledger to a database if the generative pilot earned it.
- **Quarter three.** First outcome review of ledger entries at six months; loan-fit criteria written before the summer window; pathway capacity by position for the next three seasons.
- **Quarter four.** Second bias audit reads the ledger; pathway economics to the board on one page; platform decisions taken from measured pilots; preparation for the December 2027 obligations scheduled.

WHO DOES WHAT	COMMITMENT IN THE NINETY DAYS
Academy director	Owns the plan; chairs the decision meetings that feed the ledger; presents to the board
Analyst	Two days a week: audit, ledger design, measurement data, evaluation set
Medical lead	Measurement calendar; injury and exposure logging; health-data access rules
Safeguarding lead	Video and communication policies; co-signs the pilot
Data protection adviser	Impact assessment; vendor questionnaires; consent language for families
Board	One decision: the "do not deploy" list and the budget envelope

WHAT "DONE" LOOKS LIKE ON DAY NINETY

- A register of systems, purposes and access, signed by the owner.
- A two-page bias-audit note with four charts and named decision points.
- A growth-measurement calendar with the first full round completed.
- A ledger with every consequential decision since week three, and outcome fields scheduled.
- A generative pilot with an evaluation set and a measured result.
- Completed vendor questionnaires for every supplier in discussion.
- A board-approved "do not deploy" list and a twelve-month budget in the right envelope.
- Staff trained, and the use of consumer chat tools with player data stopped.

Ninety days from now, an academy that follows this plan will have spent almost nothing and will know more about its own decisions than it has learned in the previous decade. Everything it then chooses to buy will be bought for a reason it can name.

APPENDIX A

Decision-ledger template and selection-bias audit method

Ledger fields

FIELD	CONTENT
decision_id	Unique, sequential; never reused
decision_date	Date of the meeting at which the decision was taken
player_id	Pseudonymous identifier; name resolved only in the access-controlled record
age_group · phase	Chronological group and development phase
decision_type	One of the twelve types in 1.3
birth_quarter	Q1–Q4 of the selection year
maturity_status	Early / on time / late, with method and percentage of predicted adult height at decision date
options_considered	Free text, at least two options
decision_taken	The option chosen
information_used	Links to the reviews, tests, video and data actually consulted
decision_owner	Named role accountable for the decision
participants	Roles present
reasons	Two or three sentences, written in the meeting
dissent	Any recorded disagreement and its grounds
confidence	Low / medium / high, as stated by the owner at the time
ai_assistance	Whether any system produced a recommendation or summary used in the room, and which
family_communication	Date and form of communication to the player and family
compensation_note	Any training-compensation, solidarity or sell-on implication
review_date	Scheduled date of first review
outcome_12 · 24 · 60	Status at twelve, twenty-four and sixty months: registration, level, minutes, contract, sale, injury
outcome_notes	What was learned, in one sentence

Audit method in detail

- 01 Population baseline.** Obtain the monthly birth distribution of the catchment for the relevant birth years from the national statistics office; convert to quarters of the selection year (the calendar year in most European systems, September to August in England).
- 02 Relative age.** For each age group and each intake cohort, compute the share of players by birth quarter; compare with the baseline; report the difference in percentage points and a chi-square test with effect size.
- 03 Maturity estimation.** Khamis-Roche: current height, weight and age with mid-parent height give predicted adult height; current height as a percentage of it is the maturity index, banded by convention (for example late below the 85th percentile of the age norm, early above the 96th). Mirwald: sitting height, leg length, weight and age give years from peak height velocity. Record the method; do not mix them across years.
- 04 Selection decisions.** For each season, tabulate retained, released and newly recruited players by birth quarter and maturity band; compute release rates by band; test for difference.
- 05 Exposure.** Tabulate match minutes as a share of available minutes by maturity band within each age group.
- 06 Downstream.** Track released players for three seasons: registration with another professional academy, scholarship or professional contract elsewhere; compute the "released and signed elsewhere" rate by band.
- 07 Report.** Four charts: birth-quarter share by age group against baseline; maturity-band share by age group; release rate by band; minutes share by band. One page of interpretation naming the decision points where the effect is largest; one page of interventions with owners and dates.
- 08 Repeat** at the same point each season; from year two, read decisions from the ledger rather than reconstructing them.

Maturity estimates are estimates. They are accurate enough to band players and to flag the growth spurt, not to justify a decision on their own. Where medical staff have access to skeletal-age assessment, it remains the reference method; it is not necessary for the audit.

APPENDIX B

Sources and references

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ON THE EVIDENCE

Where the text says "roughly" or "about", the underlying studies report ranges, single cohorts or self-reported results. The reader should treat every number here as a reference point for the academy's own measurement, which is the only benchmark that decides anything.

ABOUT THE AUTHOR

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Jon Soler is a football strategy, business and investment advisor, focused on the major decisions facing clubs, investors, sports organisations and public institutions.

From 2013 he built a career in international strategy consulting, reaching Associate Partner level at Oliver Wyman in Dubai and leading multi-year advisory relationships with major companies, national regulators and governments across the Middle East and Europe. His football education includes the UEFA Certificate in Football Management (UEFA Academy and University of Lausanne), a Master's in Football Management and Game Methodologies, and specialist programmes with FC Barcelona's Barça Innovation Hub and The FA. He works internationally in Spanish, English, Italian and Catalan.

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How this work continues

The playbook is designed to be applied. For an academy, a club or a national programme that wants the assessment done rather than described, the natural next step is a short, structured review: the decision inventory, the selection-bias audit, the regulatory mapping and a board note with a twelve-month plan and budget envelope, delivered in about four weeks with the academy's own people doing the measuring. Scope and terms are agreed after a conversation about the decisions the institution most needs to improve.

Selected samples of the author's analytical work are available on request.

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- Football ownership and capital: acquisition strategy, due diligence support, post-investment priorities
- Sovereign and football ecosystems: how governments, leagues and federations build and organise the game

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EDITION

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The scarce asset in an academy is not data and it is not models. It is a reliable record of what was decided, why, with what information, and what happened next.