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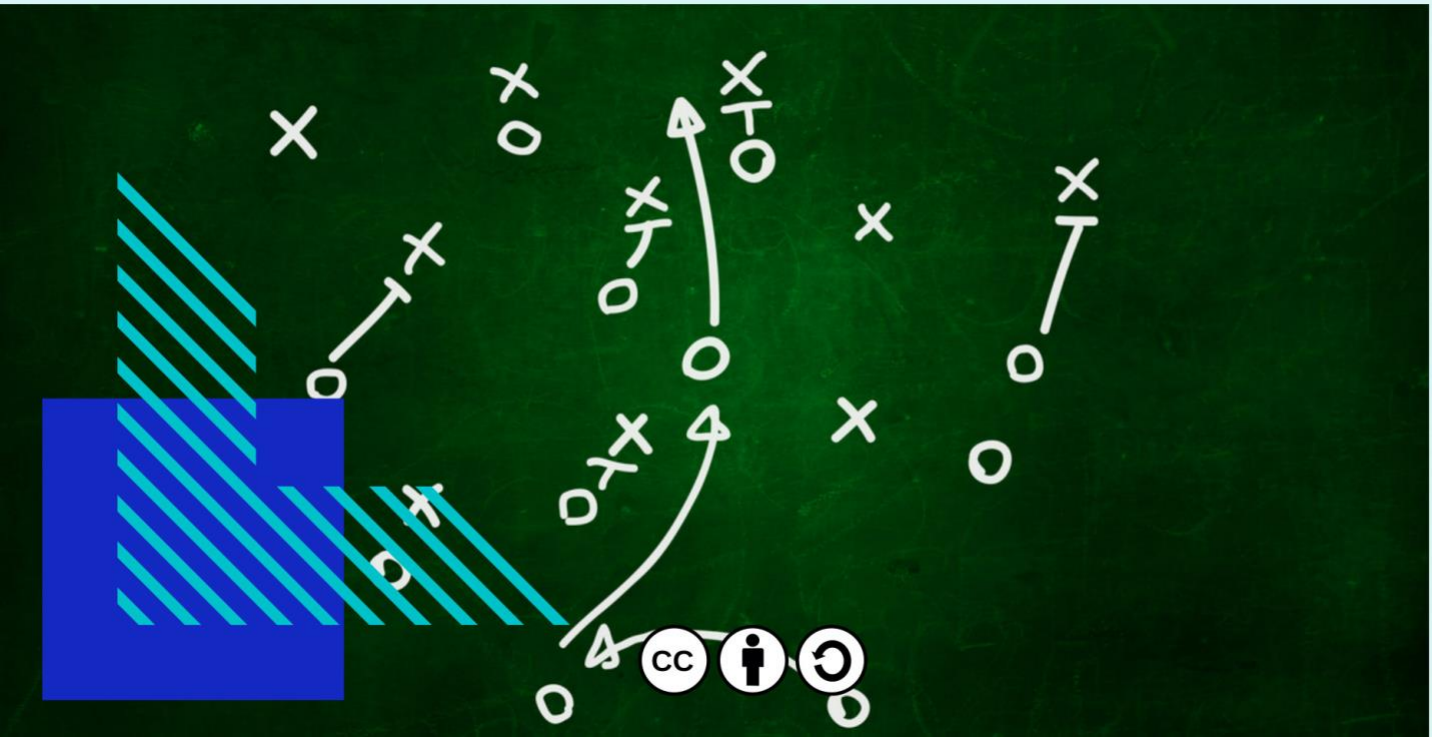
Talenttech

D2.3 Case Studies on the Application of Sports Technologies

Project Output 3: Case Studies on the Application of Sports Technologies

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1. Introduction

1.1 Purpose of this document

This collection brings together twelve case studies that show how sports technologies are applied in football, in three parts. Part A (Cases 1–3) presents three research-based cases with measurable results from peer-reviewed studies. Part B (Cases 4–9) presents six practitioner cases from Poland and the Netherlands, based on structured interviews and platform data. Part C (Cases 10–12) presents three practice examples from Lithuanian football organisations, supplied by LFF. Every case covers four elements: background information on the setting, a description of the technology used, an assessment of impact with measurable outcomes, and lessons learned and best practices.

Each case also gives learners key takeaways and three reflection exercises, so that the material can be used for active learning and not only for reading.

1.2 Target audience

The case studies are written for football academy professionals who already use, or are considering, sports technologies in talent identification, player monitoring and training. They are meant to be engaging and accessible for readers without a research background: every case opens with a one-page summary ("Case at a glance"), technical terms are explained where they first appear, and every number is linked to the published source it comes from.

1.3 Relationship to other TalentTECH outputs

This collection is one of the Work Package 2 training resources, alongside *Project Output 1: Curriculum for Integrating Sports Technologies into Player Development* (D2.1) and *Project Output 2: E-Learning Modules on Sports Technologies* (D2.2).

1.4 Method: how the cases were selected

The cases were selected against three criteria:

- **Peer-reviewed, real-world data.** Each case is based on an article in a peer-reviewed journal that reports data collected in a real football setting: a professional youth academy, a professional club and a regional youth selection team.
- **Measurable outcomes.** The source reports numerical results, not only descriptions.
- **Thematic coverage.** One case for each TalentTECH theme: AI-supported scouting and talent identification; wearable technology for monitoring and preventing injury risk; and video analysis for tactical decision-making.

The content of each case is limited to what the published source reports. Where a detail is not reported, the case does not state it. Annex A lists each value used in this document and where in the source it was checked.

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The criteria above apply to Part A. Parts B and C use a different evidence base: practitioner interviews, platform data and organisational practice accounts. These cases are not peer-reviewed. Their tables report only the figures given in the source, and Annex A covers Part A only.

1.5 Limitations

- **Different settings.** Case 1 comes from a professional youth academy, Case 2 from the first team of a professional club and Case 3 from a regional under-14 selection team. Results from one setting cannot be assumed to transfer directly to another.
- **Associations, not proof.** Cases 1 and 2 describe how well models predicted decisions or injuries in past data. Case 3 measures short-term effects within training sessions. None of the cases shows long-term effects on player development or injury rates.
- **Different evidence levels.** Part A is based on peer-reviewed studies; Parts B and C are based on interviews, platform data and organisational accounts with mostly qualitative outcomes. Results from the three parts should not be pooled.

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PART A Research-based cases (Cases 1–3)

Part A presents three cases based on peer-reviewed articles that report measurable outcomes from real football settings.

CASE 1 **TalentTECH theme: AI-supported scouting and talent identification**

2. Machine learning to predict selection decisions in a German professional youth academy

CASE AT A GLANCE

Setting
A professional German youth soccer academy; data from a seven-year period; U12 to U19 age groups

Technology
Supervised machine-learning classifiers, including XGBoost, applied to multidisciplinary player data

Sample
409 male players; 980 data points

Key result
The XGBoost models reached a ROC-AUC of 0.69 and an F1-score of 0.84. Physical, physiological and soccer-specific skill parameters were the most important for selection to the next age group

Source
Altmann et al. (2024), Journal of Sports Sciences, 42(24), 2481–2494 – peer-reviewed

2.1 Background: the academy

Every season, a youth academy decides which players move up to the next age group and which players leave. This case looks at those decisions in a professional German youth soccer academy over a seven-year period (Altmann et al., 2024).

Data were collected from 409 male players in the U12 to U19 age groups, giving 980 data points. The study followed a mixed-longitudinal approach (Altmann et al., 2024). The authors are affiliated with TSG ResearchLab, TSG 1899 Hoffenheim, the Karlsruhe Institute of Technology and the consultancy d-fine (Altmann et al., 2024). The abstract does not name the academy.

2.2 Technology used

The academy's player data covered seven domains (Altmann et al., 2024):

- physical and physiological parameters, such as linear sprint, change-of-direction sprint, countermovement jump and aerobic speed reserve;
- skill-related parameters, such as a soccer-specific skill measure;

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- psychological parameters, such as motive structure, motive attention, motive competition and cognitive flexibility;
- health-, age- and position-related parameters.

The researchers trained **supervised machine-learning classifiers** to predict whether a player would be selected or de-selected for the next age group (Altmann et al., 2024). A supervised classifier learns from past cases whose outcome is already known. **XGBoost** is one such method: it combines many small decision trees into one model.

Two measures describe how well the model worked. The **ROC-AUC** shows how well a model separates two groups: 0.5 is no better than chance and 1.0 is perfect separation. The **F1-score** combines how many of the model's predictions were correct (precision) and how many of the real cases it found (recall).

2.3 Impact assessment and measurable outcomes

The XGBoost models reached a ROC-AUC of 0.69 and an F1-score of 0.84 (Altmann et al., 2024). Physical, physiological and skill-related parameters were the most important for being selected or de-selected, across the whole sample and in all age groups. Most psychological parameters were of medium importance, and no clear pattern was found for health-, age- and position-related parameters (Altmann et al., 2024).

Table 1. Measurable outcomes reported for Case 1

Measure	Reported result	Source
Players and data	409 male players (U12–U19); 980 data points over seven years	Altmann et al. (2024)
Outcome predicted	Selected or de-selected for the next age group	Altmann et al. (2024)
Discrimination (ROC-AUC)	0.69 (XGBoost models)	Altmann et al. (2024)
F1-score	0.84 (XGBoost models)	Altmann et al. (2024)
Most important parameters	Linear sprint, change-of-direction sprint, countermovement jump, aerobic speed reserve; soccer-specific skill	Altmann et al. (2024)
Medium importance	Most psychological parameters (motive structure, motive attention, motive competition, cognitive flexibility)	Altmann et al. (2024)
No clear pattern	Health-, age- and position-related parameters	Altmann et al. (2024)

A 2026 systematic review helps to place this result. It included 27 studies that applied machine learning to youth talent identification in team sports, 13 of them in soccer. Reported ROC-AUC values

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ranged from about 0.58 to 0.96. Calibration was rarely reported, external validation was uncommon, and risk of bias was high in 59% of the studies (Tang et al., 2026).

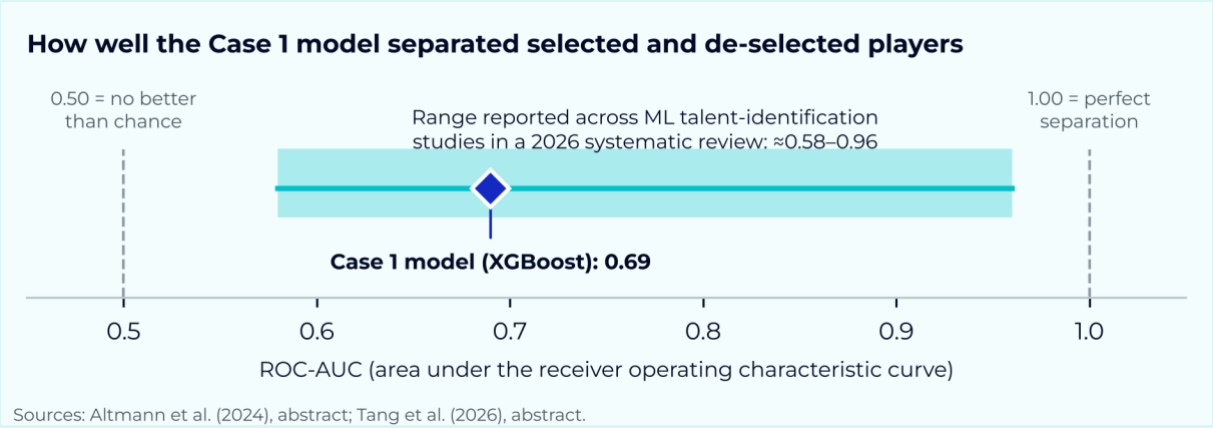


Figure 1. ROC-AUC of the Case 1 model compared with the range reported in a 2026 systematic review (Altmann et al., 2024; Tang et al., 2026).

2.4 Lessons learned and best practices

The authors conclude that their study provides insights into key parameters for talent selection and contributes to an overall talent management strategy. In particular, coaches and key stakeholders might focus on physical, physiological and skill-related parameters (Altmann et al., 2024).

The 2026 review adds three points for practice (Tang et al., 2026):

- machine learning should complement, not replace, traditional talent identification and act as a decision-support tool;
- it can help with early screening, individual progression modelling and evidence-based talent forecasting;
- models need transparent reporting, calibration checks and testing on new data before they are relied upon.

TalentTECH editorial recommendation – not from the source

A ROC-AUC of 0.69 means that the model separated selected from de-selected players better than chance, but far from perfectly. Results of this kind are best used to check whether selection decisions are consistent with the test data an academy already collects, and to open staff discussions about individual players.

Before relying on any AI scouting tool, ask the provider for its discrimination and calibration results, and whether the tool was tested on players outside the data it was built on. This note reflects the view of the TalentTECH authors, not a finding of the source.

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KEY TAKEAWAYS

- Machine learning can show which of many player measures are most closely linked to an academy's own selection decisions.
- In this academy, physical, physiological and soccer-specific skill parameters mattered most across all age groups.
- The model's ROC-AUC of 0.69 shows a useful but limited ability to separate selected from de-selected players.
- Across published studies, models are rarely tested on new data; treat them as decision support, not as a replacement for staff judgement.

REFLECTION EXERCISES

1. Which physical, physiological, skill, psychological and health data does your academy record for every age group, and how consistently?
2. If a model told you that sprint and jump results were linked to past selection decisions, what would you check before changing how you select players?
3. Which three questions would you ask a provider of an AI scouting tool about how its model was tested?

2.5 Scope and limitations

- **How the case addresses the theme.** The case applies machine learning to real academy data to support selection decisions. It is a research analysis, not an evaluation of a commercial scouting product.
- Because the model predicts the academy's own past selection decisions, it describes what those decisions were associated with. It does not show which players later became successful adult players.

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3. GPS-based prediction of injury risk at a Polish professional club

CASE AT A GLANCE

Setting
KKS Lech Poznań, PKO BP Ekstraklasa (Poland); spring round of 2020/2021 and fall round of 2021/2022

Technology
Catapult Vector S7 GPS units (10 Hz) with tri-axial accelerometer, gyroscope and magnetometer (100 Hz); three decision models: expert rules, fuzzy rules and XGBoost

Sample
36 outfield players (average age 24); 1,064 events, of which 371 events with 31 injuries formed the test set

Key result
On the test set, the XGBoost model reached accuracy 90.0%, precision 92.0%, recall 97.6% and F1-score 94.7%; the expert rule-based model reached accuracy 0.76

Source
Piłka et al. (2023), Sensors, 23(3), 1227 – peer-reviewed, open access (CC BY)

3.1 Background: the club

The case comes from KKS Lech Poznań, a club in the Polish top division (PKO BP Ekstraklasa). In the autumn round of the 2020/2021 season the team combined the domestic league, a UEFA club competition and the Polish Cup, with matches at weekends and in midweek. In the fall round before the testing period, the team suffered more than 30 injuries over five months (Piłka et al., 2023).

The club and researchers from Adam Mickiewicz University in Poznań set out to build a tool that reports an increased risk of non-contact lower-body injury for each player in the coming training week, or microcycle (Piłka et al., 2023). Data were collected from 36 players of all outfield positions, with an average age of 24, during the spring round of 2020/2021 and the fall round of 2021/2022 (Piłka et al., 2023).

3.2 Technology used

Players wore Catapult Vector S7 units in fitted vests during training and matches. The units record GPS at 10 Hz and include a tri-axial accelerometer, gyroscope and magnetometer at 100 Hz (Piłka et al., 2023). After each session, coaches marked and cleaned the data in the Catapult OpenField software. The data were then sent to a cloud application and to a database that also stored the medical reports (Piłka et al., 2023).

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From the Catapult parameters, the physical preparation coaches selected seven, including high-speed running (above 19.8 km/h), accelerations, decelerations, total player load and field time. Data were aggregated for each microcycle and for up to three microcycles before it (Piłka et al., 2023).

Three decision models were built and compared (Piłka et al., 2023):

- **Expert rule-based model.** Six rules written with the coaches. For example, an **acute:chronic workload ratio (ACWR)** between 0.80 and 1.30 adds no risk points, while a ratio above 1.60 or below 0.50 adds the maximum of 10. An average score of 6.5 or more triggers an injury alert. The ACWR compares a player's recent load with the load he has been used to.
- **Fuzzy rule-based model.** 34 rules that allow softer boundaries between load levels, built with the Simpful Python library.
- **Machine-learning model (XGBoost).** 500 decision trees, tested with 5 × 10 cross-validation. Because the training data held 657 non-injury and only 36 injury events, the injury cases were oversampled with the SMOTE technique.

3.3 Impact assessment and measurable outcomes

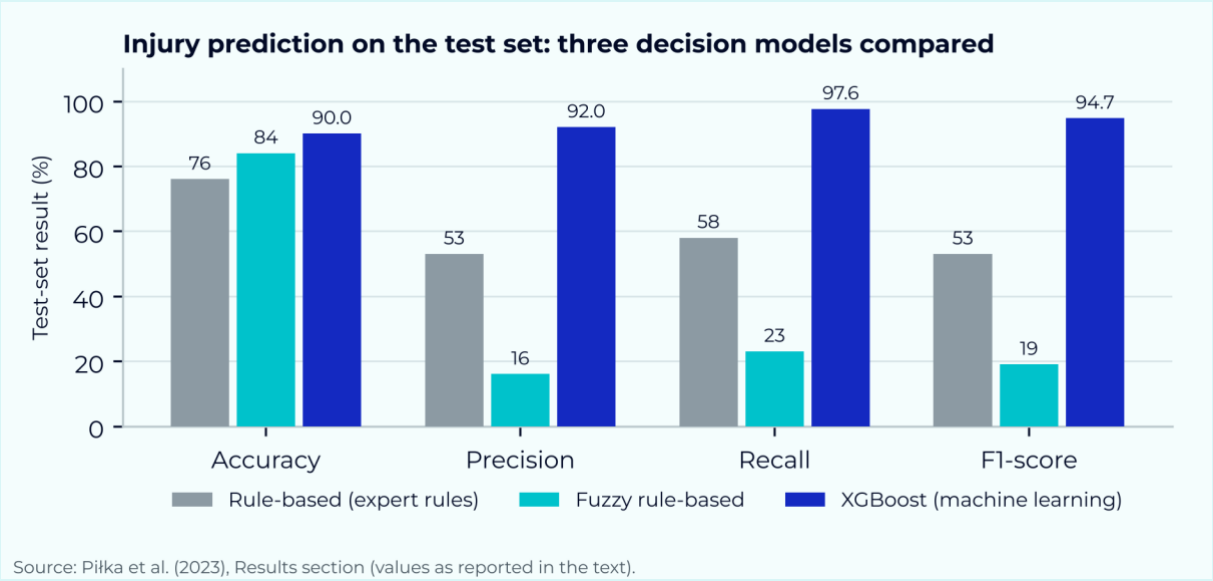
All three models were tested on the same separate test set of 371 events, including 31 injuries (Piłka et al., 2023). The authors define precision as the share of events marked "injury" that were correct, and recall as the share of all injuries that the model found.

Table 2. Test-set results reported for Case 2

Model	Accuracy	Precision	Recall	F1-score	Source
Expert rule-based	0.76	0.53	0.58	0.53	Piłka et al. (2023)
Fuzzy rule-based (65 false alarms)	0.84	0.16	0.23	0.19	Piłka et al. (2023)
XGBoost (all features and rules)	90.0%	92.0%	97.6%	94.7%	Piłka et al. (2023)

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Source: Piłka et al. (2023), Results section (values as reported in the text).

Figure 2. Accuracy, precision, recall and F1-score of the three models on the test set; values reported as proportions are shown as percentages (Piłka et al., 2023).

The XGBoost model gave the most weight to four measures: a player's total training time two microcycles before the week analysed, the number of decelerations, the number of accelerations and the distance covered at 19.8–25.2 km/h in the current microcycle. The physical training coaches confirmed these features (Piłka et al., 2023).

3.4 Lessons learned and best practices

The authors draw the following conclusions (Piłka et al., 2023):

- all three models can give early alarms about incorrectly selected training loads; the rule-based model tended to flag an injury in the week before it occurred;
- false alarms must be kept low, because they can lead to a player being kept out of training or a match without good reason; the XGBoost model had a low false-positive rate;
- load should be judged over several weeks, not only the current week, in line with the ACWR approach;
- accelerations and decelerations deserve particular attention; braking load was the hardest to recreate in compensatory training for players with fewer than 45 match minutes, so the club added eccentric strength training on machines.

TalentTECH editorial recommendation – not from the source

The case shows that wearable data become useful when they are linked to medical records and to rules the coaches understand. An academy starting with GPS units can begin with simple, transparent rules on week-to-week load changes, agreed with its coaches, and add machine learning once several seasons of clean load and injury data exist.

An alert is best treated as a prompt to review a player's plan with staff, not as an automatic decision to remove the player from training. This note reflects the view of the TalentTECH authors, not a finding of the source.

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KEY TAKEAWAYS

- GPS and inertial sensor data, linked to medical reports, can be used to flag players at higher risk of non-contact lower-body injury.
- On one club's test data, a machine-learning model clearly outperformed expert and fuzzy rules.
- Load in earlier weeks, accelerations and decelerations were among the most informative measures.
- Prediction is only the first step: the club linked the findings to concrete training measures, such as eccentric strength work.

REFLECTION EXERCISES

1. Which load measures could your academy record reliably in every session, and who would link them to the medical records?
2. Your model flags a key player before a match. Who decides what happens next, and what information do they need?
3. How would you explain to a coach why a false alarm and a missed injury have different costs?

3.5 Scope and limitations

- **How the case addresses the theme.** The case uses wearable data to monitor injury risk and support prevention. It does not show that injuries fell as a result.
- The players were professional first-team players, not academy players; youth players may respond to load differently.
- The data come from one club and two league rounds, and include external load only; heart rate, perceived exertion and previous injuries were not included (Piłka et al., 2023).
- The article reports slightly different XGBoost values in its abstract (precision 92.4%, recall 96.5%, F1-score 94.4%) and in its Results section. This document uses the Results-section values (see Annex A).

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CASE 3 TalentTECH theme: Video analysis for tactical decision-making

4. Video priming before small-sided games in an under-14 regional selection team

CASE AT A GLANCE

Setting
An under-14 regional selection team made up of the most skilled players from seven local clubs, preparing for a national tournament; competitive period of the 2022–2023 season (January–February)

Technology
Four-minute priming videos shown on a laptop before small-sided games; GPS tracking (10 Hz) and video-based notational analysis of every action

Sample
24 male players (age 13.8 ± 0.4 years; 7.5 ± 2.3 years of football experience); 1,642 actions analysed

Key result
After the offensive video, passing decisions and passing execution were better than in the control condition (0.90 vs 0.83 and 0.79 vs 0.67); after the creative video, players explored more space (7.11 m vs 5.62 m)

Source
Coutinho et al. (2025), Frontiers in Psychology, 16, 1553561 – peer-reviewed, open access

4.1 Background: the team

The case involved an under-14 regional selection team. The team was made up of the most skilled players from seven local clubs, selected by experienced coaches to compete in a national tournament. The players trained three times a week for 90 minutes with their clubs and played 11-a-side matches at weekends (Coutinho et al., 2025).

Twenty-four male players took part, with a mean age of 13.8 ± 0.4 years and 7.5 ± 2.3 years of football experience. Data were collected in four sessions during the competitive period of the 2022–2023 season, in January and February (Coutinho et al., 2025).

4.2 Technology used

Before each small-sided game, players watched one of three conditions (Coutinho et al., 2025):

- **Control:** no video.
- **Offensive priming:** a four-minute video of teams such as Barcelona or Manchester City building up play from the back through sustained possession.
- **Creative priming:** a four-minute video of individual creative passes, dribbles and shots by well-known players.

Two expert coaches with UEFA Pro and UEFA A licences selected the videos. Each team watched on a 16-inch laptop near the sideline during the five-minute recovery between games. The games were 6-

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a-side plus goalkeepers on a 64 × 43 m pitch and lasted five minutes each. The order of conditions was randomised for each session, and coaches gave no feedback during play (Coutinho et al., 2025).

Performance was measured in two ways (Coutinho et al., 2025):

- **GPS tracking** (FieldWiz, 10 Hz) recorded each player's position and movement. From these data the researchers calculated distances to the nearest teammate and opponent, a **spatial exploration index** (how much of the pitch a player used) and distances covered.
- **Video and notational analysis.** A camera filmed every game, and an expert analyst tagged 1,642 actions in Metrica Sports' Play software. Decision-making and execution were rated with the Game Performance Evaluation Tool (GPET), and creativity with the Creative Behavior Assessment in Team Sports (CBATS). Repeat-coding agreement was high (kappa 0.72–0.89 for GPET and 0.83–0.92 for CBATS).

4.3 Impact assessment and measurable outcomes

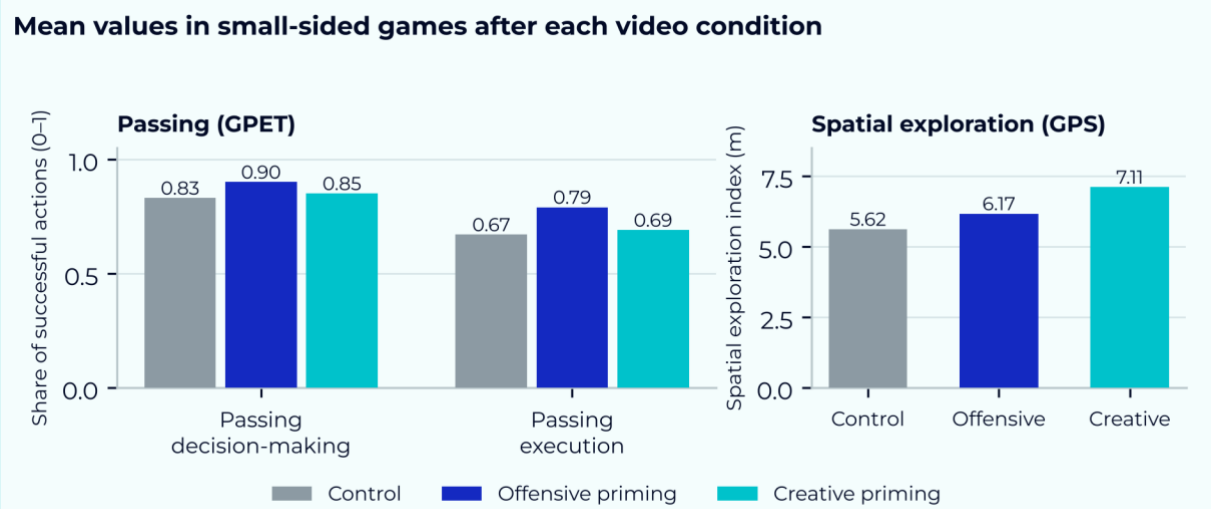
The offensive video led to better passing decisions and passing execution than both the control and creative conditions. The creative video led to more spatial exploration and more shooting attempts. Both video conditions increased the distance players covered compared with the control condition (Coutinho et al., 2025).

Table 3. Measurable outcomes reported for Case 3 (mean values, n = 24)

Measure	Control	Offensive	Creative	Reported test (Coutinho et al., 2025)
Passing decision-making (share of successful decisions)	0.83	0.90	0.85	$\chi^2 = 18.6$, $p < 0.001$; offensive higher than control ($d = 0.58$)
Passing execution (share successful)	0.67	0.79	0.69	$\chi^2 = 13.2$, $p = 0.001$; offensive higher than control and creative
Dribbling deception (share)	0.27	0.65	0.37	Offensive higher than control ($p = 0.032$, $d = 0.7$) and creative ($p = 0.001$)
Spatial exploration index (m)	5.62	6.17	7.11	$\chi^2 = 6.10$, $p = 0.047$; creative higher than control ($d = 1.14$) and offensive ($d = 0.9$)
Shooting attempts (mean count)	0.04	0.07	0.17	$\chi^2 = 7.05$, $p = 0.029$; creative higher than control and offensive
Total distance covered (m)	255.64	296.49	300.17	$p < 0.001$; control lower than both video conditions (small effects)

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Source: Coutinho et al. (2025), Tables 1 and 2 (n = 24 players).

Figure 3. Passing performance and spatial exploration after each video condition (Coutinho et al., 2025).

4.4 Lessons learned and best practices

The authors describe video-based priming as an accessible tool for youth football (Coutinho et al., 2025):

- videos that show collective ball possession can be used to encourage better passing decisions and execution;
- videos of creative actions may encourage players to explore space and to try new shooting patterns;
- the creative video did not increase creative passing or dribbling, possibly because individually focused clips did not match the collective nature of the game, and four minutes without verbal guidance from a coach may not have been enough.

TalentTECH editorial recommendation – not from the source

Short priming clips need little equipment: the researchers used one laptop at the side of the pitch. Coaches could build their own four-minute clips that match the tactical principle of a session, such as building up from the back, and then watch whether passing choices change in the next game.

Because the study measured effects within single sessions, it does not show lasting learning; checking this over several weeks would be a separate step. This note reflects the view of the TalentTECH authors, not a finding of the source.

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KEY TAKEAWAYS

- Four minutes of video between games changed how young players passed and moved in the next small-sided game.
- A video of collective possession play was linked to better passing decisions and execution.
- A video of creative individual actions was linked to more spatial exploration and shooting attempts, but not to more creative passing or dribbling.
- GPS tracking and structured video coding made it possible to measure tactical behaviour, not just to describe it.

REFLECTION EXERCISES

1. Which tactical principle in your next session could you prime with a short video, and which clips would you choose?
2. How could you measure whether players' passing decisions change after the video, using the tools your academy has?
3. The creative video did not change creative passing. What would you add, such as coach guidance or matching game rules, to link the video to the session goal?

4.5 Scope and limitations

- **How the case addresses the theme.** The case uses video to shape tactical decisions and uses video analysis to measure them. It shows short-term effects within sessions, not long-term learning.
- All three conditions were played on the same day, so one condition may have influenced the next; the authors suggest one condition per day in future studies (Coutinho et al., 2025).
- Teams watched the videos together, so peer influence during viewing was not controlled; the sample was one male under-14 team (Coutinho et al., 2025).
- The authors note that better attacking play may partly reflect players paying less attention to defending (Coutinho et al., 2025).
- For passing decision-making, the article's Table 2 gives $p = 0.049$, while its abstract and Results text report $\chi^2 = 18.6$, $p < 0.001$. Table 3 above uses the text values (see Annex A).

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PART B Practitioner cases from Poland and the Netherlands (Cases 4–9)

Six case studies show how sports technologies are used, and where they fail, across the full ladder of football: from a preschool group to an Ekstraklasa first team and the Eredivisie. Each case maps to one module of the D2.1 Curriculum and ends with key takeaways and reflection exercises for the learner.

Five cases come from structured practitioner interviews held in September–October 2026. One comes from PlayMaker Pro's own platform data (2026). All five curriculum modules are covered. The cases can be used as the case-analysis task (40% of the M1 assessment) or as discussion material in facilitated workshops.

Table 1. Overview of the cases

#	Case	Organisation and level	Technology	D2.1 module
1	Physical-intensity-first scouting	Cracovia Kraków, Ekstraklasa	Skill Corner, StatsBomb, scouting data platforms	M1 Digital scouting
2	One analytics platform for three jobs	Legia Warszawa, Ekstraklasa	Wyscout, Opta, StatsBomb via API	M2 Performance analytics
3	Rewarding progress, not rank	PlayMaker Pro, youth players	PM Score, weekly ranking graphic	M2 Performance analytics
4	Load monitoring through the player's eyes	FC Groningen, Wellington Phoenix	GPS vests, heart rate, strength testing	M3 Wearables
5	Video and a club platform at U12–U13	Odra Opole academy, 1st League club	Veo camera, ProTrainUp	M4 Video analysis
6	When simpler methods win	Piast Strzelce Opolskie, Tygrysek Academy	PZPN certification workflow; none for ages 4–6	M5 Integration

CASE 4 **TalentTECH theme: AI-supported scouting and talent identification (M1 Digital scouting)**

5. Cracovia Kraków: physical-intensity-first scouting with a data stack

CASE AT A GLANCE

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Setting
Cracovia Kraków, Ekstraklasa (Poland); the club's first scout, since November 2023

Technology
Skill Corner (physical data), StatsBomb and a scouting data platform (statistics), internal report template, Transfer Room

Sample
One scout; 11 leagues; about 3,500 first-team players per window

Key result
Data filters make this coverage possible for one scout; live observation remains compulsory

Source
Structured practitioner interview, September–October 2026 (interviewee role: scout)

5.1 Background: the club

Cracovia hired its first scout in November 2023. He covers Scandinavia (including second divisions in Norway, Sweden and Denmark), the second and third levels in France and Germany, and the Ekstraklasa. He has written 649 reports.

About 11 leagues × 350 players cannot be watched live. Without paid platforms, physical data on foreign players comes from agents, who may present it selectively.

5.2 Technology used

- **One tool per job.** Skill Corner provides physical data (top speed, intensity). StatsBomb and a scouting data platform provide statistics. An internal template produces reports, and Transfer Room handles market contacts.
- **One reference scale.** Each attribute is scored 1–5 against the Ekstraklasa: 3 = mid-table level, 4 = upper half, 5 = would stand out in stronger European leagues. Players are graded A (play from day one or high resale value), B (squad player or development bet) or C (doubts, keep observing).
- **Seasonal rhythm.** October is spent watching and flagging, with about three sentences per player per match. November is spent writing full reports.
- **Character checks.** References are gathered from former coaches about how the player behaves when he is not in the starting XI.

5.3 Impact assessment and measurable outcomes

The club buys fast, high-intensity profiles that larger clubs want. In one transfer, the club identified a forward mainly through his top speed (about 35 km/h), bought him cheaply and sold him at a significant profit six months later.

No other quantified impact was reported in the interview; for this reason no chart is given.

Table 4. Quantitative information reported in the Case 4 interview

Measure	Reported information	Source

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Measure	Reported information	Source
Leagues covered	11	Interview (2026)
Players per window	About 3,500 first-team players	Interview (2026)
Reports written	649	Interview (2026)
Rating scale	1–5 (Ekstraklasa reference); A/B/C grade	Interview (2026)
Example transfer	Top speed about 35 km/h; sold at a profit after 6 months	Interview (2026)

5.4 Lessons learned and best practices

The interviewee describes data as narrowing the search while the scout makes the decision. A shared reference scale is what makes players from different leagues comparable.

TalentTECH editorial recommendation – not from the source

Create a shared scale that rates players from 1 to 5 against your own league, and grade every player A, B or C: A means sign now, B means keep following, C means leave for now. Split watching and report writing into separate periods; take short notes while watching and write the full report later. Flag physical data supplied by agents separately, and never put a player in the top group before he has been watched live at least once. Make references from former coaches on how the player behaves when he is not starting part of the assessment.

KEY TAKEAWAYS

- Data narrows the search; the scout makes the decision.
- A shared benchmark scale is what makes players from different leagues comparable.
- Physical data without platform coverage is only as reliable as its source.

REFLECTION EXERCISES

1. Which three physical or statistical filters would match your club's game model?
2. Where does your data on foreign or lower-league players come from, and could it be biased?
3. Write one natural-language search query you wish your scouting tool could answer.

5.5 Scope and limitations

- **How the case addresses the theme.** The case shows how data platforms filter candidates in scouting. The interviewee sees AI not as a tool in use today but as a future support that will filter candidates, not choose them.
- The data stack is a budget decision; smaller clubs cannot afford it.

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- Every attribute still needs a written comment, which costs time.
- The player must still be seen live.
- The case is based on one scout's experience.

CASE 5 **TalentTECH theme: Performance analytics (M2)**

6. Legia Warszawa: one analytics platform for three jobs

CASE AT A GLANCE

Setting
Legia Warszawa, Ekstraklasa (Poland); opponent preparation up to Champions League level

Technology
Wyscout, Opta and StatsBomb feeding one in-house system through APIs; the club's own metrics

Sample
The club's analysis department

Key result
The bottleneck is no longer collecting data but choosing which data matters

Source
Structured practitioner interview, September–October 2026 (interviewee role: analysis department)

6.1 Background: the club

Legia's analysis department is led by a Head of Analysis who works directly with the first-team head coach. Under him are two analyst-coaches and a data analyst. The team prepares for opponents up to Champions League level.

Behind every tactical trait of an opponent, such as its pressing or build-up, sit many small packets of data. Selecting and connecting them is now the hard part.

6.2 Technology used

- **One data layer.** Wyscout, Opta and StatsBomb feed one in-house system through APIs, together with the club's own metrics. The same data serves analysis of the club's own game, opponent analysis and scouting. Because all three use one set of definitions, the conclusions stay consistent.
- **Workflow driven by the game model.** Analysts choose from a fixed set of tools rather than building new ones each week. The work runs in a weekly cycle.
- **Two outputs per opponent.** A full report goes to the staff. A 2–3 minute version goes to the players.
- **Paired roles.** Each analyst works with a coach: the lead analyst with the first assistant, individual analysts with individual coaches.

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6.3 Impact assessment and measurable outcomes

A single data definition keeps the conclusions of own-game analysis, opponent analysis and scouting consistent. The output for players is cut to 2–3 minutes.

No other quantified impact was reported in the interview; for this reason no chart is given.

Table 5. Quantitative information reported in the Case 5 interview

Measure	Reported information	Source
Analysis team	1 Head of Analysis, 2 analyst-coaches, 1 data analyst	Interview (2026)
Data providers	3 (Wyscout, Opta, StatsBomb) + club metrics	Interview (2026)
Player version	2–3 minutes per opponent	Interview (2026)
Interviewee's view	Roughly half of results depend on budget and player quality	Interview (2026)

6.4 Lessons learned and best practices

The interviewee describes how one data definition across scouting and match analysis prevents conflicting conclusions, and why the output must be shrunk for its audience.

TalentTECH editorial recommendation – not from the source

Write the definitions of the metrics you use for match analysis and scouting on a single page, so that everyone understands each term in the same way. Focus on one game question each week and look only at the data that answers it. Prepare a detailed report for the staff and three short messages for the players that they can remember on the pitch. Pair the person who prepares the data with a coach, so that the analysis goes straight into training.

KEY TAKEAWAYS

- A single data definition across scouting and match analysis prevents conflicting conclusions.
- Shrink the output for the audience: players get minutes, not reports.
- The scarce skill is selection: deciding which numbers explain a tactical problem.

REFLECTION EXERCISES

1. Do your scouting and match analysis use the same metric definitions?
2. Cut your last opponent report to three points a player could remember on the pitch.
3. Which decision in your academy would you never hand to an algorithm, and why?

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6.5 Scope and limitations

- **How the case addresses the theme.** The case shows how performance analytics is organised at a top club. The interviewee sees AI as a support in selecting data, never as the decision-maker.
- Results often do not reflect performance; in the interviewee's view, roughly half of results depend on budget and player quality.
- A gap named by the interviewee: coaches are still hired through contacts and recommendations rather than profiled by data, the way players are.
- An analysis team of this size is not realistic for small academies.

CASE 6 **TalentTECH theme: Performance analytics (M2)**

7. PlayMaker Pro: rewarding progress, not rank

CASE AT A GLANCE

Setting
PlayMaker Pro's community group for its most engaged youth players (aged roughly 15–24)

Technology
PM Score (a 0–100 rating calculated from match data), weekly ranking graphic

Sample
Youth players using the platform

Key result
A ranking of the largest score gains, not the highest scores, keeps lower-rated players in the conversation

Source
PlayMaker Pro platform data (2026)

7.1 Background: the platform

PlayMaker Pro runs a community group for its most engaged youth players. Each player has a PM Score, a 0–100 rating calculated from match data. The question was how to share performance data with players without discouraging most of them.

A ranking by absolute score rewards the same few players every week. Most players would never appear, and the data would demotivate them rather than guide them.

7.2 Technology used

- **The change is the headline.** Each round, a graphic shows the five largest score increases, for example +7 (from 65 to 72). The gain is the largest number on the graphic; the before and after scores are secondary.
- **The scale makes small gains visible.** The progress bar runs from 40 to 90 rather than 0 to 100, so a 7-point gain is visible.

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- **Recognition rewards effort, not status.** Recognition goes to progress, consistency and comebacks. There is no award for a high score.
- **Every score comes with an action.** A score result is always paired with a development tool and a re-test date, for example a 7-day sprint on a weak area.
- **The thumbnail test.** At 300 px wide, the graphic must still show the title, the leading player's name and the gain.

7.3 Impact assessment and measurable outcomes

No impact result (such as a measure of engagement or motivation) was reported in the source; the case describes a design approach.

Table 6. Quantitative information reported in the Case 6 source

Measure	Reported information	Source
Score range	PM Score 0–100	PlayMaker Pro (2026)
Player age	About 15–24	PlayMaker Pro (2026)
Shown on the graphic	Five largest gains per round	PlayMaker Pro (2026)
Example gain	+7 (from 65 to 72)	PlayMaker Pro (2026)
Progress bar	40–90 scale	PlayMaker Pro (2026)
Thumbnail test	300 px width	PlayMaker Pro (2026)

7.4 Lessons learned and best practices

The case shows that how data is framed changes behaviour as much as the data itself, and that every number should be linked to a next step.

TalentTECH editorial recommendation – not from the source

When you show data to young players, put progress first, not the highest score. Because players who start with a low score improve more easily, do not put all recognition under one heading; reward the most improved and the most consistent player separately. Add to every score the topic the player will work on and the date of the next test. In graphics, show the change as the largest number and set the scale so that small gains are visible. Do not share a ranking of minors without parental consent, and give players who do not want to appear on the list the right to opt out.

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KEY TAKEAWAYS

- How data is framed changes behaviour as much as the data itself.
- Show the change over time; that is what a young player controls.
- Link every number to a next step; a score without an action is only a label.

REFLECTION EXERCISES

1. Which metric could you share with your U15 group that rewards improvement?
2. How would you present the same data to a parent, a player and a coach?
3. What safeguards do you need before publishing any ranking of minors?

7.5 Scope and limitations

- **How the case addresses the theme.** The case explains through a platform design how performance data can be presented to young players.
- Gains are easier at lower starting scores, so the ranking favours players who start lower.
- Public ranking of minors needs consent and a clear opt-out.
- The case comes from the coordinating partner PlayMaker Pro's own platform; it is not an independent evaluation.

CASE 7 **TalentTECH theme: Wearable technology for monitoring and preventing injury risk (M3)**

8. FC Groningen and Wellington Phoenix: load monitoring through the player's eyes

CASE AT A GLANCE

Setting
FC Groningen (Eredivisie, Netherlands) and Wellington Phoenix (New Zealand); the interviewee is a professional forward

Technology
GPS vests, heart-rate monitoring, strength testing on machines

Sample
One player's experience at two clubs

Key result
90% of the player's own baseline strength was the threshold that decided who joined full training

Source
Structured practitioner interview, September–October 2026 (interviewee role: professional forward)

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8.1 Background: the team

The interviewee is a professional forward who has played in Germany, the Netherlands, Poland, South Korea and New Zealand. He is currently with FC Groningen in the Eredivisie. He is the end user of monitoring technology, not its operator.

Clubs want to monitor a player's training load and make the return from injury safe. But which load is measured depends on the technology used.

8.2 Technology used

- **FC Groningen.** GPS vests and heart-rate monitoring feed a six-zone training-load system. Staff set each player's running targets for the session. Each player is compared against his own baseline from year to year, and players can see their data.
- **Wellington Phoenix.** A return-to-play protocol measured leg strength on machines. A player below 90% of his baseline strength did not join full training.

8.3 Impact assessment and measurable outcomes

In the interviewee's experience, players below the threshold who trained anyway got injured.

No injury rate or other quantified impact was reported in the interview; for this reason no chart is given.

Table 7. Quantitative information reported in the Case 7 interview

Measure	Reported information	Source
Return-to-full-training threshold	90% of the player's own baseline leg strength (Wellington Phoenix)	Interview (2026)
Training-load zones	6 zones (FC Groningen)	Interview (2026)
Basis of comparison	The player's own year-to-year baseline (FC Groningen)	Interview (2026)

8.4 Lessons learned and best practices

The interviewee describes how comparing a player with his own baseline rather than a team average, and using a simple threshold rule, works in practice. He also stresses that loads the sensors do not measure must be taken into account.

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TalentTECH editorial recommendation – not from the source

Record each player's strength and sprint values at the start of the season and compare the player with these values, not with the team average. Set a simple rule for return from injury, such as "a player does not join full training before reaching 90% of his own strength", and apply it without exception. Note separately the loads that GPS does not measure, such as headers, duels and falls, especially for forwards and centre-backs. Let players see their own data and ask them regularly how they feel. Put in a written rule which data goes with a player when he leaves the club.

KEY TAKEAWAYS

- Compare each player with his own baseline, not with a team average.
- A simple threshold rule (90% of baseline) can be more useful than a complex dashboard.
- Know what your sensors miss: running load is not total load.

REFLECTION EXERCISES

1. Which load in your sessions is invisible to your current tools?
2. Design a return-to-play rule your academy could run without expensive equipment.
3. Who owns a player's monitoring data, and what leaves with him when he transfers?

8.5 Scope and limitations

- **How the case addresses the theme.** The case describes, through the player's eyes, how wearable technology and strength testing are used in load monitoring and return-to-play decisions. It is one player's experience, not club data.
- GPS measures running. It does not count headers, kicks per foot, physical contacts or falls. For a tall target forward, this impact load drives uneven muscle strain; his own physiotherapist pointed this out.
- Which technology a club uses depends on the coaching staff's preferences and the budget, not on what the player needs.
- There is no common standard across leagues. Injury history moves with a transferred player, but no rules govern who owns the data.
- The player prefers human match analysis to apps. A lost match can still show strong individual numbers.

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9. Odra Opole academy: video and a club platform at U12–U13

CASE AT A GLANCE

Setting
Odra Opole academy; the club plays in the Polish 1st League (second tier)

Technology
Veo match camera, ProTrainUp club platform (in use for seven years)

Sample
One coach's U12–U13 groups

Key result
Conversations with players and parents rest on footage and facts, not memory

Source
Structured practitioner interview, September–October 2026 (interviewee role: youth coach and scout)

9.1 Background: the academy

Odra Opole plays in the Polish 1st League, the second tier. The interviewee has coached youth football for 15 years, mainly U12–U13, and also scouts for the first team. The club sits in the middle of Polish football: more resources than grassroots clubs, far less than the Ekstraklasa.

9.2 Technology used

- **One club platform (ProTrainUp, in use for seven years).** It combines parent communication, player statistics (minutes, goals, involvement) and a training library organised by training cycles. It is also used for planning and reviewing sessions.
- **Session planning from the archive.** Coaches browse club-wide and personal session archives to avoid repeating themes. They share session outlines with players in advance.
- **Video (Veo camera).** Matches and training sessions are recorded. Selected clips go to players and parents as evidence alongside the statistics.

9.3 Impact assessment and measurable outcomes

Parents see minutes and involvement directly, so less coach time goes into verbal reporting. Feedback conversations rest on observable behaviour. In the coach's words, having everything in one place makes the job easier.

No other quantified impact was reported in the interview; for this reason no chart is given.

Table 8. Quantitative information reported in the Case 8 interview

Measure	Reported information	Source

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Measure	Reported information	Source
Coaching experience	15 years, mainly U12–U13	Interview (2026)
Platform in use	7 years (ProTrainUp)	Interview (2026)
Clips for the player's own review	3 per match are enough	Interview (2026)

9.4 Lessons learned and best practices

The interviewee describes how, at youth level, the value of video lies in the feedback conversation rather than in tagging every event, and how a shared session archive builds a club-wide methodology.

TalentTECH editorial recommendation – not from the source

If you have no analyst, mark clips during the match, so you do not have to watch the whole match again afterwards. Three short clips per player are enough: one good action, one mistake and one decision moment. Choose clips linked to that week's training theme and share session plans with players in advance. Keep session plans in a club-wide shared archive, so that knowledge stays in the club even when a coach changes. Before sharing footage of children with parents, get written consent and decide where the videos are stored and for how long.

KEY TAKEAWAYS

- At youth level, the value of video lies in the feedback conversation, not in tagging every event.
- A shared session archive is low-tech, but it builds a club-wide methodology.
- Fewer clips, chosen with intent, beat a full match replay; for the player's own review, three clips per match are enough.

REFLECTION EXERCISES

1. Choose three clips from your last match: one strength, one mistake, one decision.
2. What would parents need to see to stop asking about minutes played?
3. Which consent rules apply when you share video of minors outside the club?

9.5 Scope and limitations

- **How the case addresses the theme.** At this level, video supports feedback rather than coded tactical analysis. The case shows how video analysis for tactical decisions is simplified at youth level.
- There is no analyst, so clip selection depends on the coach's time.
- Recording 12–13-year-olds and sharing clips with parents requires clear consent rules.

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10. Piast Strzelce Opolskie and Tygrysek Academy: when simpler methods win

CASE AT A GLANCE

Setting
Piast Strzelce Opolskie (small-town club) and Tygrysek Academy (preschool, ages 4–6)

Technology
Polish Football Association (PZPN) certification workflow, training-planning app; no technology for ages 4–6

Sample
One coach's experience in two settings

Key result
At a small academy, the biggest digital win was removing paperwork, not adding AI

Source
Structured practitioner interview, September–October 2026 (interviewee role: academy coordinator and coach)

10.1 Background: the academy

The interviewee coordinated the academy at Piast Strzelce Opolskie, a small-town club, for many years. He ran its documentation for the national federation's bronze academy certificate. He now coaches preschool children (ages 4–6) at Tygrysek Academy.

Certification requires session plans, player records and progress reports. Even though federation systems are online, documents are still printed, signed, scanned and uploaded.

10.2 Technology used

- **A half-digital workflow.** The interviewee's proposal: an electronic signature through the federation profile that every licensed coach already has.
- **Unexpected good practice.** Certification created a culture of regular session planning at clubs that had none. A training-planning app kept that habit alive after the audit.
- **A hard limit on technology.** For ages 4–6, the priorities are play, social skills and basic movement. The interviewee sees this limit as a matter of principle, not a temporary technology gap.

10.3 Impact assessment and measurable outcomes

The certification process created a habit of regular session planning at clubs, and a planning app kept that habit alive after the audit.

No other quantified impact was reported in the interview; for this reason no chart is given.

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Table 9. Quantitative information reported in the Case 9 interview

Measure	Reported information	Source
Age group (Tygrysek)	Ages 4–6	Interview (2026)
Certificate level	Bronze academy certificate (Polish Football Association)	Interview (2026)

10.4 Lessons learned and best practices

The interviewee describes why digitalisation should start where the pain is, and why knowing when not to use technology is a competence in its own right. At this age coaches mainly need soft skills; in his view the larger gap is educating parents about children's nutrition and recovery.

TalentTECH editorial recommendation – not from the source

Start digitalisation not by buying a new tool but by easing the task that wastes the most time. Identify the steps where documents are printed, signed and scanned again, and make them fully digital. Use standards such as the federation certificate to build the habit of regular session planning, and keep that habit with a simple planning app. Before starting any new technology, write down its cost, the staff time it needs and when you would stop using it. For ages 4–6, focus on play, social skills and basic movement instead of technology, and inform parents about nutrition and rest.

KEY TAKEAWAYS

- Start where the pain is: automate repetitive administration before buying performance technology.
- An external standard can drive adoption of digital tools more than the tools themselves.
- Knowing when not to use technology is a competence in its own right.

REFLECTION EXERCISES

1. Which recurring administrative task in your academy costs the most hours per month?
2. At which age group would you introduce data or video, and what would come first?
3. Draft a three-step plan to introduce one technology in your setting, with the cost, the staff time and the stop criteria.

10.5 Scope and limitations

- **How the case addresses the theme.** The case deals with integrating technology into academy management through an administrative workflow and a deliberate limit.
- The proposed electronic signature is the interviewee's proposal, not an implemented solution.
- The case rests on one coach's experience and contains no quantified impact.

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PART C Lithuanian practice examples (Cases 10–12)

Part C presents three practice examples from Lithuanian football organisations, supplied by LFF. They show how organisations of different sizes and operating models use technology in everyday work.

The cases are organisational practice accounts, not peer-reviewed studies. Tools still under development are described as such and are not presented as deployed.

CASE 10 **TalentTECH theme: Integrating video analysis, player monitoring and AI tools**

11. Vilnius Football Academy: integrating video, player monitoring and emerging AI tools

CASE AT A GLANCE

Setting
Vilnius Football Academy (VFA), Vilnius, Lithuania; youth players U6–U18 and a men's team in the second division

Technology
Systematic video analysis; player attendance and wellbeing tracking; proprietary video-analysis software and AI/computer-vision applications under development; internal management platform under development

Sample / scale
Over 1,000 young athletes; more than 50 specialists (organisational scale, not evaluation sample)

Key result
The academy reports more standardised player evaluation, better workload oversight and faster feedback; no quantified before-and-after effects are provided.

Source
LFF, CASES_TalentTECH_LFF.docx (organisational practice account; not peer-reviewed)

11.1 Background: the academy

VFA operates a pathway from early childhood through youth football to a senior men's team. Its stated goal is to use technology within a common development methodology rather than as a stand-alone add-on.

11.2 Technology used

- **Video analysis.** The academy already uses video to review team tactics and individual player actions and to provide feedback.
- **Attendance and wellbeing tracking.** A dedicated system tracks attendance and self-reported fatigue, muscle soreness, stress, mood and perceived exertion (RPE).

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- **Tools under development.** VFA is developing proprietary match-event tagging and individual reporting tools, as well as AI/computer-vision functions for player tracking, automated event recognition and statistical reporting with technology partners. Its internal management platform is also under development. These planned features should not be described as fully deployed.

11.3 Impact assessment and measurable outcomes

Reported operational benefits include more consistent player assessments, improved visibility of workload and player wellbeing, clearer identification of strengths and development needs, and a faster feedback cycle.

The supplied account gives no player-level dataset, comparison group, numerical effect sizes, injury incidence, or validated predictive accuracy. It therefore supports an implementation case, not a causal claim that AI improved sporting outcomes.

Table 10. Quantitative information reported in the Case 10 source

Measure	Reported information	Source
Young athletes	Over 1,000 (organisational scale)	LFF (2026)
Specialists	More than 50	LFF (2026)
Age groups	U6–U18 and a men's team in the second division	LFF (2026)
Quantified impact	Not reported	LFF (2026)

11.4 Lessons learned and best practices

- Start with a concrete coaching or operational problem.
- Keep coaches responsible for interpreting data and making player decisions.
- Introduce new functions through small pilots and phased integration.

TalentTECH editorial recommendation – not from the source

To bring video, wellbeing data and management information together under one development methodology, first write down which coaching decision each type of information will serve. Review the fatigue, soreness and RPE values that players report each day in the same meeting as the weekly video feedback, so that performance and load are seen together. Try the AI and computer-vision tools under development in a small pilot with one age group first, and compare the automatic tagging with the coach's own tagging to find its errors. Keep tools in use and tools under development on separate lists, and show only the tools in use as results in reports. Set parental consent and storage rules before collecting data and footage of young players.

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KEY TAKEAWAYS

- A connected approach can combine video, wellbeing and operational information.
- AI event recognition and predictive injury modelling are future ambitions, not demonstrated outcomes in this case.
- Human review remains essential even when data collection becomes more automated.

REFLECTION EXERCISES

1. Which player-development decision would benefit most from combining video evidence and wellbeing data?
2. What minimum indicators would you collect to test whether a new reporting tool improves feedback speed or consistency?
3. How would you pilot computer-vision tagging while checking errors and protecting youth-player data?

11.5 Scope and limitations

- Organisational self-report; no documented research protocol or quantitative impact evaluation.
- Development-stage software and future ambitions cannot be treated as current validated capabilities.

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CASE 11 **TalentTECH theme: Wearable technology for monitoring and preventing injury risk; video analysis**

12. FK Minija: using wearable and video data to support resource-efficient decisions

CASE AT A GLANCE

Setting
FK Minija, Lithuania; first team in LFF I Lyga, reserves in LFF II Lyga B Division and youth academy U6–U18

Technology
Catapult GPS, Polar heart-rate monitors, ITERPRO, LiveTag.PRO, PSD, Wyscout, Veo CAM 3, HUDL, drones, Go3 cameras, Veo automated clips and basic match statistics

Sample / scale
Approximately 250 academy players (organisational scale, not evaluation sample)

Key result
The club reports more objective workload review and automated alerts for potential overtraining; no reduction in injuries or model performance metrics is reported.

Source
LFF, CASES_TalentTECH_LFF.docx (organisational practice account; not peer-reviewed)

12.1 Background: the club

FK Minija combines senior and youth operations and seeks to make efficient use of limited staff time across teams.

12.2 Technology used

- **Video workflow.** LiveTag.PRO, Wyscout and recording systems such as Veo CAM 3, HUDL, drones and Go3 cameras for goalkeeper training. Movavi and DaVinci support editing.
- **Physical load.** Catapult GPS and Polar heart-rate devices provide physical-load information. ITERPRO processes self-reported RPE and workload indicators and generates alerts for possible overtraining or elevated injury risk.
- **Automated video.** Veo's AI package automates clip selection and baseline match statistics; the club says its AI coaching-advice feature still needs development before it becomes substantially useful.

12.3 Impact assessment and measurable outcomes

The club describes a shift towards data-supported squad and workload decisions and reports that automatic alerts help staff review potentially excessive loads.

No number of monitored sessions, alerts, injuries, false positives, or measured changes in injury rates is supplied. Alerts should therefore be treated as decision prompts, not as proven injury predictions.

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Table 11. Quantitative information reported in the Case 11 source

Measure	Reported information	Source
Academy players	Approximately 250 (organisational scale)	LFF (2026)
Age groups	U6–U18	LFF (2026)
Team levels	First team LFF I Lyga; reserves LFF II Lyga B Division	LFF (2026)
Quantified impact	Not reported	LFF (2026)

12.4 Lessons learned and best practices

- Allocate staff time to interpret data; collection alone does not change practice.
- Use automation to reduce routine workload, particularly where staffing is limited.
- Evaluate alert usefulness and false alarms before basing training restrictions on them.

TalentTECH editorial recommendation – not from the source

For every automatic load alert, put in writing who reviews it and what extra information is checked before a session is changed, for example the player's reported RPE, his minutes in the last match and the medical staff's view. Log the alerts in a table and, after a few weeks, compare which ones pointed to a real problem and which were false alarms. Read GPS, heart rate and RPE together rather than one by one; a rise in a single indicator is not enough for a decision. Note each week how much time automatic clip selection saves the coach, so you can see which tools really work.

KEY TAKEAWAYS

- A practical mix of wearable, RPE and video tools can support staff with limited resources.
- Automated alerts require contextual review by coaches and medical personnel.
- More sophisticated readiness predictions using sleep, nutrition and psychology are prospective ideas, not established results.

REFLECTION EXERCISES

1. Who reviews an ITERPRO alert and what additional information is needed before changing a session?
2. Which indicators could show whether automated clip generation actually saves coaches time?
3. How would you audit false alarms and missed problems in workload monitoring?

12.5 Scope and limitations

- Practice-based account without a controlled study or measured injury-prevention effect.

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- The described systems operate across different squads; the source does not specify a consistent evaluation cohort or measurement period.

CASE 12 **TalentTECH theme: Video analysis for tactical decision-making**

13. FK Žalgiris Football Academy: structured video analysis for player development

CASE AT A GLANCE

Setting
FK Žalgiris Football Academy, Lithuania; boys' and girls' youth development, U6–U18

Technology
Veo video recording and review; longitudinal footage archive; standardised coach assessments supported by video evidence

Sample / scale
No number of participating players or coded actions reported

Key result
The academy reports more consistent evaluation and clearer tactical feedback; no quantified improvement in decisions or performance is provided.

Source
LFF, CASES_TalentTECH_LFF.docx (organisational practice account; not peer-reviewed)

13.1 Background: the academy

The academy develops boys and girls from grassroots to elite youth levels and emphasises a shared approach to evaluating progress.

13.2 Technology used

- **Veo video system.** Veo is the academy's main technology: staff film training and matches, review individual and team actions and share relevant footage with players.
- **Longitudinal archive.** The footage is retained to document development over time.
- **Standardised assessments.** Coaches use standardised assessments and cross-reference them with video evidence. The academy does not currently report using AI scouting software or wearable sensors for injury prevention.

13.3 Impact assessment and measurable outcomes

The academy reports more objective evaluations, more consistent coaching criteria and faster preparation for matches. It also reports that players understand tactical feedback better when it is supported by visual examples.

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The source supplies no test scores, number of sessions, independent coding reliability or comparison between video and non-video coaching. These are qualitative observations rather than measured causal effects.

Table 12. Quantitative information reported in the Case 12 source

Measure	Reported information	Source
Age groups	U6–U18, boys and girls	LFF (2026)
Players or coded actions	Not reported	LFF (2026)
Quantified impact	Not reported	LFF (2026)

13.4 Lessons learned and best practices

- Apply a small set of tools consistently before expanding the technology stack.
- Define the coaching objective before selecting a platform.
- Invest in coach skills and retain coach responsibility for feedback and mentoring.

TalentTECH editorial recommendation – not from the source

For each age group, choose a small number of tactical behaviours to be assessed consistently with video, and write down their definitions. Once a month, have two coaches rate the same clips separately and compare the results; this shows whether the assessment criteria mean the same thing to everyone. Use the video archive not only for match analysis but to show each player's development across seasons, placing clips of the same behaviour from the start and end of the season side by side. Before sharing footage with players, especially minors, agree consent and storage rules in advance.

KEY TAKEAWAYS

- Video can provide a shared reference for feedback and long-term development reviews.
- Standardised criteria are necessary to compare observations across coaches and seasons.
- A unified AI/video/biometric player profile is a future ambition, not a currently documented system.

REFLECTION EXERCISES

1. What three tactical behaviours would you evaluate consistently using video across an age group?
2. How would you check whether two coaches rate the same video actions similarly?
3. What simple pre/post measure could test whether video-supported feedback improves player understanding?

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13.5 Scope and limitations

- No quantitative outcome study, comparison group or validated measurement instrument reported.
- The proposed integration of computer vision and biometric sensors is prospective.

14. Cross-case synthesis

Table 13 compares the three research-based cases (Part A). They differ in setting, technology and study design, but all three report measurable outcomes from real football data published in 2023 or later.

Table 13. The three research-based cases compared (Part A)

	Case 1	Case 2	Case 3
TalentTECH theme	AI-supported scouting and talent identification	Wearable technology for monitoring and preventing injury risk	Video analysis for tactical decision-making
Setting	Professional German youth academy (U12–U19)	KKS Lech Poznań first team, Poland	Under-14 regional selection team
Players and data	409 players; 980 data points; 7 years	36 players; 1,064 events; 2 league rounds	24 players; 1,642 coded actions; 4 sessions
Technology	Supervised machine learning (XGBoost)	Catapult GPS and inertial sensors; expert rules, fuzzy rules and XGBoost	Priming videos; GPS tracking; video-based notational analysis
Study design	Mixed-longitudinal analysis of selection decisions	Model development on club data, tested on a separate test set	Repeated measures; each player experienced all three conditions
Headline outcome	ROC-AUC 0.69; F1-score 0.84	XGBoost F1-score 94.7% vs 0.53 for expert rules	Passing decisions 0.90 vs 0.83 after offensive video
Source	Altmann et al. (2024)	Piłka et al. (2023)	Coutinho et al. (2025)

14.1 Research-based cases (Part A): common threads

- **Several types of data.** Case 1 combined seven data domains, Case 2 linked GPS data with medical reports, and Case 3 combined GPS tracking with video coding (Altmann et al., 2024; Piłka et al., 2023; Coutinho et al., 2025).
- **Expert knowledge stays central.** In Case 2 the risk rules were written with the coaches and the coaches confirmed the key features; in Case 3 expert coaches chose the videos. The 2026 review describes machine learning as a support for, not a replacement of, expert judgement (Piłka et al., 2023; Coutinho et al., 2025; Tang et al., 2026).

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- **The cost of errors matters.** Case 2 stresses that false alarms can keep players out of training without good reason; the review notes that calibration and external testing are rarely reported (Piłka et al., 2023; Tang et al., 2026).
- **Transfer is an open question.** Each case comes from one setting, and Case 3 measured effects within single sessions (Altmann et al., 2024; Piłka et al., 2023; Coutinho et al., 2025).

TalentTECH editorial recommendation – not from the source

Across the three cases, technology produced useful signals about selection, injury risk and decision-making, but in each case staff still had to interpret those signals and act on them. For academy professionals, the practical lesson is to plan the review process (who looks at the data, how often, and with what follow-up) as carefully as the choice of tool. This synthesis note reflects the view of the TalentTECH authors.

14.2 Practitioner cases (Part B)

All six practitioner cases point the same way: technology narrows choices and frees time, while people keep the decisions. Access, not interest, is the main barrier.

Table 14. Lessons across the practitioner cases (Part B)

Lesson	Cases	What it means for an academy
Data filters, humans decide	4, 5, 7	Use AI to build shortlists; keep live observation and the coach's judgement
Missing data is a hidden bias	4, 7	Check whose data is absent or supplied by interested parties before trusting a ranking
Compare players with their own baseline	6, 7	Track change per player; avoid team averages for development decisions
Make outputs smaller for the audience	5, 6, 8	Players get 2–3 minutes or 3 clips; staff get the full report
Budget and the coach's preferences decide adoption	4, 7, 8	Choose tools a small academy can sustain; plan for staff time, not only licences
Admin first, performance tech second	8, 9	Remove repetitive paperwork before adding sensors or AI
Minors need explicit safeguards	6, 8, 9	Consent, opt-out and a legal basis come before any ranking, recording or data sharing

14.3 Lithuanian practice examples (Part C)

The Lithuanian cases complement the research-based cases by showing how football organisations of different sizes and operating models use technology in everyday work. They should be shown as practice-based evidence, not pooled with peer-reviewed effect estimates.

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Table 15. The Lithuanian cases compared (Part C)

Dimension	VFA (Case 10)	FK Minija (Case 11)	FK Žalgiris Academy (Case 12)
Main emphasis	Integrated video, wellbeing and emerging AI	Wearables, workload alerts and multi-tool video	Consistent video-supported evaluation
Current documented practice	Video analysis and wellbeing tracking	GPS, heart rate, RPE alerts and video tools	Veo and standardised assessments
In development / envisaged	Proprietary AI/computer vision and management platform	Broader AI readiness models	Unified AI/video/biometric player profile
Evidence level	Qualitative organisational account	Qualitative organisational account	Qualitative organisational account

Shared lessons.

- Start with a specific problem and an implementation plan rather than buying technology for its own sake.
- Assign responsibility for data quality, interpretation, feedback and decisions.
- Distinguish currently used functions from tools still under development.
- Track practical indicators (for example feedback turnaround, review consistency, staff time, alert follow-up) before claiming performance improvements.

15. How to use these case studies

Task T2.3 foresees that the training materials can be used both for online learning through the PlayMaker web portal and in in-person workshops. The suggestions below are guidance from the TalentTECH authors and can be adapted.

15.1 Online learning (PlayMaker web portal)

Integration of the training resources into the PlayMaker web portal is planned under Task T2.4. A suggested self-study path for each case:

- read the “Case at a glance” box to see the setting and the main result;
- work through the background, technology and outcomes, using the figure and table to check the numbers;
- answer the three reflection exercises in writing, ideally with your own academy in mind;
- compare your answers with the key takeaways and the scope and limitations section.

15.2 In-person workshops

The cases can also be used in a face-to-face session. Table 16 gives a suggested structure for one case; timings are indicative only.

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Table 16. Suggested workshop structure for one case (about 90 minutes)

Step	Activity	Suggested time
1. Introduction	Facilitator presents the “Case at a glance” box and the theme	10 min
2. Reading	Participants read the background, technology and outcomes sections	15 min
3. Data discussion	Small groups interpret the table and figure: what does the evidence show, and what does it not show?	20 min
4. Reflection exercises	Groups work on the three exercises, applying them to their own academies	30 min
5. Plenary	Groups share answers; facilitator closes with the key takeaways and limitations	15 min

15.3 Choosing a case by role

- Scouts and talent identification staff: start with Case 1 (AI-supported scouting and talent identification), then Case 4.
- Performance and medical staff: start with Case 2 (wearable technology and injury risk), then Cases 7 and 11.
- Coaches and video analysts: start with Case 3 (video analysis and tactical decision-making), then Cases 5, 8 and 12.
- Academy managers: read the cross-case synthesis in Section 14 first, then Cases 9 and 10.

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16. References

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Annex A Verification checklist

Table A1. Verification of values against the sources

#	Value used in this document	Source and location	Status
1	Case 1: professional German youth soccer academy; seven-year period; U12–U19	Altmann et al. (2024) – abstract	Verified
2	Case 1: 409 male players; 980 data points; mixed-longitudinal approach	Altmann et al. (2024) – abstract	Verified
3	Case 1: physical, physiological, psychological, skill-, health-, age- and position-related parameters; supervised classifiers	Altmann et al. (2024) – abstract	Verified
4	Case 1: XGBoost ROC-AUC 0.69, F1-score 0.84; most important, medium and no-clear-pattern parameters	Altmann et al. (2024) – abstract	Verified
5	Case 1: author affiliations (TSG ResearchLab, TSG 1899 Hoffenheim, Karlsruhe Institute of Technology, d-fine)	Altmann et al. (2024) – bibliographic record (PubMed ID 39688281)	Verified
6	Case 1: authors' practical conclusion on physical, physiological and skill-related parameters	Altmann et al. (2024) – abstract	Verified
7	Review: 27 studies (13 in soccer); ROC-AUC ≈ 0.58–0.96; calibration rarely reported; external validation uncommon; high risk of bias in 59%; complement, not replace	Tang et al. (2026) – abstract	Verified
8	Case 2: KKS Lech Poznań; PKO BP Ekstraklasa; spring round 2020/2021 and fall round 2021/2022; 36 outfield players, average age 24	Piłka et al. (2023) – Introduction; Section 3.1	Verified
9	Case 2: congested calendar in autumn 2020/2021; more than 30 injuries over five months in the preceding fall round	Piłka et al. (2023) – Introduction	Verified
10	Case 2: Catapult Vector S7; GPS 10 Hz; accelerometer, gyroscope and magnetometer 100 Hz; OpenField; database with medical reports	Piłka et al. (2023) – Section 3.1	Verified
11	Case 2: 1,064 events; train 693 events / 36 injuries; test 371 events / 31 injuries; 657 non-injury events in training; SMOTE	Piłka et al. (2023) – Sections 3.1 and 3.4	Verified
12	Case 2: six expert rules; ACWR rule bands; alert at average ≥ 6.5; fuzzy model with 34 rules (Simpful); XGBoost with 500 trees, 5 × 10 cross-validation	Piłka et al. (2023) – Sections 3.2–3.4	Verified

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#	Value used in this document	Source and location	Status
13	Case 2: rule-based 0.76 / 0.53 / 0.58 / 0.53; fuzzy 0.84 / 0.16 / 0.23 / 0.19 and 65 false positives; XGBoost 90.0 / 92.0 / 97.6 / 94.7	Piłka et al. (2023) – Section 4 (text)	Verified. The abstract gives 92.4 / 96.5 / 94.4 for XGBoost; this document uses the Section 4 values
14	Case 2: most important features; eccentric strength training; false alarms undesirable; future data (heart rate, RPE, previous injuries)	Piłka et al. (2023) – Sections 4 and 5	Verified
15	Case 3: 24 male U14 players; 13.8 ± 0.4 years; 7.5 ± 2.3 years' experience; seven local clubs; national tournament; 3 × 90-min club sessions per week	Coutinho et al. (2025) – Methods: Participants	Verified
16	Case 3: three conditions; four-minute videos; UEFA Pro and UEFA A coaches; 16-inch laptop; 6-a-side plus goalkeepers on 64 × 43 m; 5-min games; January–February 2022–2023	Coutinho et al. (2025) – Methods: Study design; Procedures	Verified
17	Case 3: FieldWiz GPS 10 Hz; Play (Metrica Sports); GPET; CBATS; 1,642 actions; kappa 0.72–0.89 and 0.83–0.92	Coutinho et al. (2025) – Methods: Data collection	Verified
18	Case 3: spatial exploration index 5.62 / 6.17 / 7.11 m; total distance 255.64 / 296.49 / 300.17 m	Coutinho et al. (2025) – Table 1; Results text	Verified
19	Case 3: passing decision 0.83 / 0.90 / 0.85; passing execution 0.67 / 0.79 / 0.69; dribbling deception 0.27 / 0.65 / 0.37; shooting attempts 0.04 / 0.07 / 0.17	Coutinho et al. (2025) – Tables 2 and 3	Verified
20	Case 3: χ^2 and p-values for passing decision, passing execution, spatial exploration and shooting attempts; effect sizes d = 0.58, 1.14 and 0.9	Coutinho et al. (2025) – Abstract; Results text	Verified. Table 2 gives p = 0.049 for passing decision; this document uses the abstract and Results-text value
21	Case 3: limitations (same-day conditions, peer influence, attention to defending) and practical conclusions	Coutinho et al. (2025) – Discussion; Limitations; Conclusion	Verified

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