# The Execution Layer: Mechanics as the Missing Variable in Transfer Prediction

*The transfer market's predictive infrastructure operates on a single analytical layer — statistical actions — while the layer that most determines whether those actions replicate in a new environment is structural execution quality: mechanics. The data infrastructure to assess mechanics already exists. No one has built the analytical products to use it.*

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March 2026
SW-R-2026-003

KEY FINDING

> The football transfer market's predictive infrastructure operates on a single analytical layer — statistical actions — while the layer that most determines whether those actions replicate in a new environment is structural execution quality: mechanics. The field conflates what a player does, the technique they select, and the mechanical quality of their execution into a single unit of measurement. This conflation propagates through every model, composite rating, and "league exchange rate" that consumes action-level data as its input. The data infrastructure to assess mechanics already exists in football's top leagues — `29` skeletal points per player, captured at up to `100` frames per second. No one has built the analytical products to use it. Basketball has. Football has not.

01

## The Summer of Strikers

*The 2025–26 transfer window as a natural experiment*

The 2025–26 Premier League summer transfer window produced the most concentrated test of transfer prediction in the competition's history. English clubs spent over `£3 billion` in total, with six high-profile forwards alone — Alexander Isak, Benjamin Sesko, Viktor Gyökeres, Hugo Ekitike, João Pedro, and Nick Woltemade — costing a combined `£471 million` [1]. Liverpool broke the British transfer record twice in a single window. Manchester United, Arsenal, Chelsea, and Newcastle each staked their seasons on the assumption that forward-line investment would resolve attacking deficiencies that had cost them the previous campaign.

By November, the results were stark. Isak, Sesko, and Gyökeres — the three most expensive of the six — had scored a combined `six` league goals between them [2]. Erling Haaland, the benchmark, had scored fourteen in the same period. By January 2026, Gyökeres had been described as struggling to match the technical level of Arsenal's other attackers [3]. Sesko, despite possessing the physical tools that made him one of the most coveted young forwards in Europe, was managing two goals in seventeen league appearances [4]. Isak, signed for `£125 million`, had recorded a single shot on target in his opening four league appearances before suffering a season-disrupting injury [5].

The conventional explanation arrived on schedule. Analysts cited "adaptation time." Dr Ian Graham, Liverpool's former director of research, has described a "league exchange rate" — an expected percentage drop in per-90 output when a player moves between leagues. A forward arriving from

Portugal's Primeira Liga can expect approximately a **35%** average decline in output on a per-90 basis [6]. The adjustment is statistical: take a player's actions in the source environment, apply a discount, project the residual into the target environment.

This is the analytical machinery the market relies on. It is also, we assess, operating on the wrong unit of analysis entirely.

02

## Three Layers, One Metric

*What the transfer market measures — and what it misses*

The transfer prediction infrastructure — from scouting databases to composite models to league exchange rates — measures a single layer of player performance: **actions**. Goals scored, assists provided, expected goals generated, passes completed, duels won. These are countable events with measurable frequencies. They are the data that populates every scouting platform and every algorithmic shortlist in professional football.

Actions tell you **what** a player does, and how often. They do not tell you how the player executes those actions, or — critically — whether the execution quality that produced those actions in one environment will produce equivalent actions in another.

Beneath the action layer sit two further layers, each carrying distinct information about a player's capability and each with different implications for transferability.

**Technique** is the method a player selects to complete an action. A striker presented with a scoring opportunity might drill the ball, curl it to the far post, toe-poke, or side-foot. A defender contesting an aerial situation might jump early for positioning advantage or time a late attack on the ball. Technique tells you **how** a player attempts to complete an action. It adapts to tactical context — a team that emphasises direct play will demand different technical selections from a team that builds through the thirds. Technique is context-sensitive.

**Mechanics** is the physical execution quality within a technique. It is how the body generates force, manages balance, times contact, and recovers position. Mechanics tells you **why** a particular technique succeeds or fails under specific physical conditions. A striker's shooting mechanics — the compactness of their release, the position of their standing foot, the degree of follow-through — determine whether they can reliably generate power, accuracy, and shot speed. Unlike technique, which adapts to tactical instruction, mechanics are grounded in a player's physical structure, training history, and neuromuscular patterning. They are more stable than either actions or technique across environmental changes.

The distinction is consequential: **actions are the most context-dependent layer and mechanics the most context-independent, yet the entire transfer prediction infrastructure is built on the context-dependent layer.**

A player's goal tally in Portugal is a function of the Portuguese league's defensive standards, the player's team quality, the tactical system, the quality of service, and the player's own capability. When that player moves to England, every contextual factor changes simultaneously. The league exchange rate attempts to adjust for this by applying a blanket discount derived from historical transfer outcomes. But the discount is applied to the action — the aggregate output — without any ability to isolate the component of that output that is genuinely portable: the player's execution quality.

03

## Why Mechanics Transfer and Statistics Do Not

*Context dependency across the three layers*

The claim that mechanics is the strongest predictor of skill transfer between footballing environments rests on a structural argument about what each layer of performance carries across a change in context.

**Actions are environmental products.** A striker's goal record is the joint output of their own ability, their teammates' ability to create chances, the opposition's defensive quality, the tactical system's ability to position the striker in dangerous areas, and the volume of minutes played. Change the environment and every input to the goal record changes simultaneously. The action-level data from the source environment is, at best, a noisy proxy for the player's underlying capability. At worst, it is systematically misleading — inflated by a weaker league, deflated by a dysfunctional team, or distorted by a tactical system that created artificial volume.

**Technique is partially portable.** A player can adapt their technical selections to new tactical demands — learning to play one-touch in a possession system, or to play longer balls in a direct system. But the speed of adaptation and the ceiling of adaptation depend on the mechanical substrate. A player whose reception mechanics involve an open body shape and a directional first touch can adapt to a high-tempo pressing environment. A player whose reception mechanics involve a closed body shape and a controlling first touch will struggle in the same environment regardless of tactical instruction.

**Mechanics are the most stable layer.** A player's striking mechanics, tackling form, aerial contest positioning, and running gait are products of years of physical development, coaching, and neuromuscular patterning. They do not reset when a player changes clubs. A compact shooting release that generates power from a short backlift will produce powerful shots in Lisbon, London, and Leipzig. A wide shooting release that requires a long backlift to generate equivalent power will be closed down more easily in environments with faster defensive recovery — not because the player has declined, but because the mechanical profile has encountered a context that exposes its limitation.

> **The layer of player performance least dependent on the environment is the layer most likely to persist when the environment changes. The transfer market's analytical infrastructure is built on the layer most dependent on it.**

04

## The Compounding Stack

*How the omission propagates through the analytical pipeline*

The absence of mechanical assessment does not merely leave a gap in the scouting process. It propagates through every analytical layer that consumes action-level data as its input, and each layer adds the appearance of rigour without correcting the original omission.

THE COMPOUNDING STACK

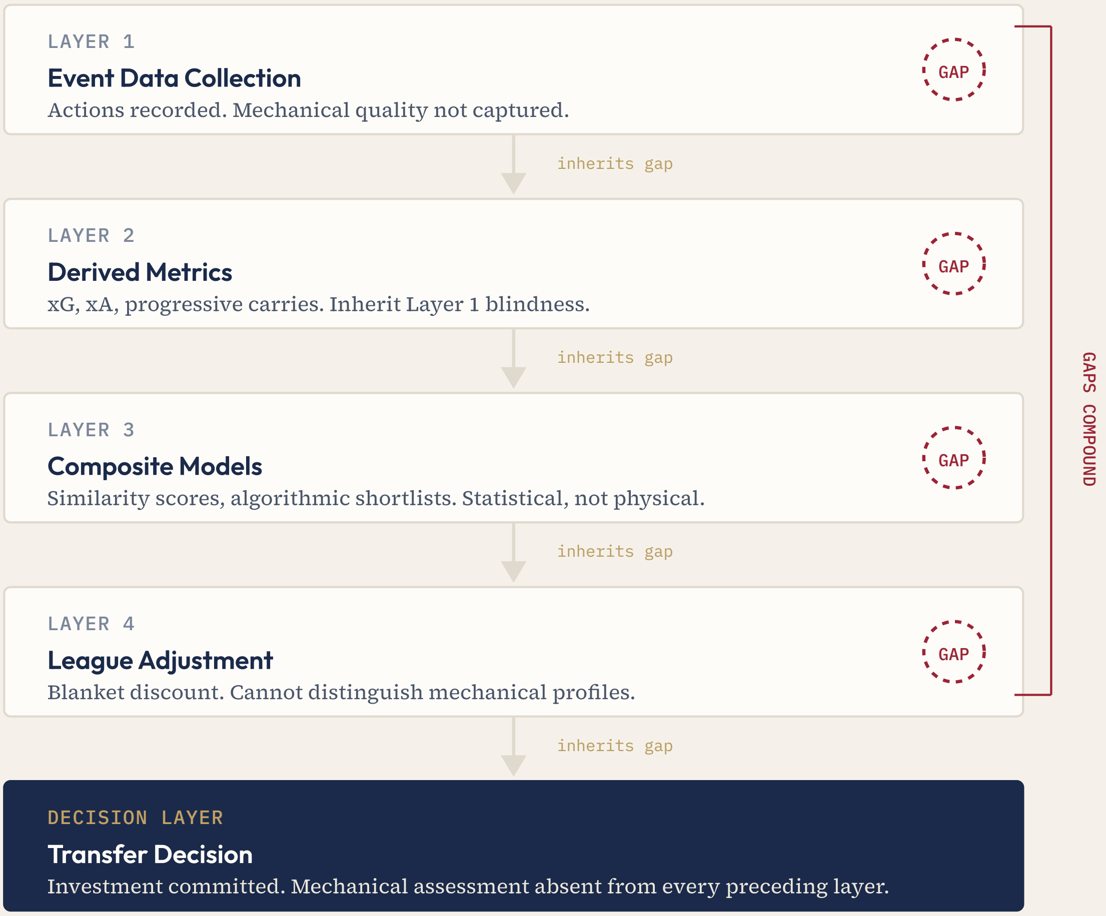


**Fig. 1.** Each layer adds analytical sophistication without correcting the foundational omission. The mechanical quality of a player's execution — the variable most predictive of whether actions replicate in a new environment — is absent from the event data and remains absent through derived metrics, composite models, league adjustment, and the transfer decision itself.

**Layer 1: Event data collection.** Providers record actions — passes, shots, duels, carries. Each recorded event is an action-level observation. The mechanical quality of the action is not captured. Two shots that arrive at the same location with the same xG value may have been produced by fundamentally different mechanical profiles — one compact and repeatable, the other requiring a full backlift that will be closed down in faster defensive environments. The event record does not distinguish between them.

**Layer 2: Derived metrics.** Expected goals, expected assists, progressive carrying distance, and similar metrics aggregate action-level events into per-90 rates or cumulative values. These metrics inherit the blindness of the event data they consume. A player's xG per 90 in one league is treated as a measure of their shooting capability, but it is in fact a measure of their shooting outcomes in a specific set of conditions. The mechanical capability that produced those outcomes — which may be more or less transferable than the outcomes suggest — is invisible to the metric.

**Layer 3: Composite models.** Scouting platforms combine derived metrics into composite player ratings, similarity scores, and algorithmic shortlists. These models operate entirely within the action layer. A model that identifies a player as "similar to" a successful Premier League striker on the basis of comparable xG, progressive carries, and aerial duel rates has no mechanism for assessing whether the underlying mechanical profiles are comparable. The similarity is statistical, not physical.

**Layer 4: League adjustment.** The league exchange rate — the expected drop in per-90 output when transitioning between leagues — is the most revealing symptom of the architectural flaw. The adjustment is a blanket discount applied to the action-level aggregate. It has no mechanism for distinguishing between a player whose mechanical profile predicts successful transfer and a player whose mechanical profile predicts failure. Both receive the same discount, because the variable that separates them is not in the model.

**Layer 5: The transfer decision.** The club's decision-makers consume the output of layers 1 through 4 and commit investment. At no point in the standard analytical pipeline has anyone assessed whether the player's mechanical execution quality is suited to the demands of the target environment.

Each layer adds analytical sophistication to an input that carries a structural omission. The omission is categorical: the entire pipeline measures the wrong unit of analysis for the question it is trying to answer. The question is "will this player's capability transfer to a new environment?" The pipeline answers "what did this player do in their current environment, adjusted for historical averages?" The distance between these questions is where transfer value is destroyed.

05

## Same Statistic, Different Mechanics, Different Prediction

*Where action-level data produces identical readings for divergent profiles*

The analytical value of mechanical assessment is most visible where action-level data produces identical readings for players whose physical execution — and therefore whose transferability — diverges entirely.

Consider two Premier League right-backs, both statistically effective tacklers, both deployed in elite systems. Their tackle completion rates, duels won per 90, and defensive action success rates overlap substantially. The action-level data says: equivalent defenders.

The mechanical assessment says something different. The first player contests primarily by using his frame, positioning shoulder-to-shoulder and leveraging upper-body strength. His tackling mechanics are sprint-intensive — he needs to be alongside the attacker before initiating the contest. Post-tackle, the ball is typically retained and the next possession begins immediately. This mechanical profile predicts success in a high-line defensive system where the defender is the last line and the team requires immediate transition from defence to possession. It predicts difficulty in a low-block system where tackles are contested from deeper positions at tighter angles.

The second player challenges on the ground using either foot and from a wider range of angles. His post-tackle outcome is different: from deeper positions, the ball typically goes out of bounds; from higher positions, it ends up loose. He absorbs significant physical punishment — knocks, falls, trampling — requiring a calm, unfazed temperament. This mechanical profile predicts success in a compact, disruptive defensive system — a pressing trap, an insurance role in rest-defence. It predicts difficulty in a possession-first system where tackle outcomes need to initiate the next sequence [7].

This is not a question that action-level data can answer. The tackle completion statistics are comparable. The mechanical profiles are orthogonal. A club signing either player on the basis of defensive statistics alone has a 50% chance of acquiring a mechanical profile that matches their system's demands — and no tool in the standard analytical pipeline to improve those odds.

The same principle operates in attacking play. Viktor Gyökeres arrived at Arsenal from Sporting CP having scored 39 league goals in a single season [8]. His physical profile mapped to what Arsenal lacked: pace, power, willingness to run in behind. Yet by January 2026, observers described him as losing possession cheaply and squandering opportunities by taking too many touches [3]. Arsenal reportedly acknowledged before signing him that they would need to adapt their style to accommodate his profile [9]. The statistical scouting identified the right player for the role but could not predict the mechanical mismatch with the system.

Recent research provides the first empirical evidence that skeletal data captures what event data cannot. Van Haaren et al. (2025), analysing **1,736** one-on-one dribbles from the 2022–23 Champions League using Hawk-Eye SkeleTRACK data (29 anatomical landmarks at 25 Hz), found that defender posture and attacker balance were among the most impactful variables for predicting dribble outcomes — variables entirely invisible to standard event data [10]. This is the first published study using multi-camera skeletal match data for a performance prediction task in football, and it directly validates the thesis that mechanical information carries predictive power that action-level statistics do not.

06

## The Data Exists. The Products Do Not.

*Football's skeletal tracking infrastructure — and the NBA comparison*

The conventional assumption — that football lacks the data infrastructure for biomechanical assessment — is wrong. The infrastructure exists. What does not exist is anyone using it for this purpose.

Since 2022, every Premier League match has been captured by Genius Sports' optical tracking system at up to **100** frames per second, recording **29** skeletal points per player in three dimensions. For semi-automated offside technology (SAOT), the system generates up to **10,000** mesh data points per player — hundreds of millions of data points per match [11]. Since the 2025–26 season, every Bundesliga match has been captured by TRACAB's Gen5 system at **50** frames per second, recording **21** skeletal points per player in 3D, producing **140 million** data points per match [12]. Hawk-Eye's SkeleTRACK captures 29 skeletal points at 50 fps across FIFA and UEFA competitions [13].

| DIMENSION | NBA (2025–26) | BUNDESLIGA (2025–26) | PREMIER LEAGUE (2025–26) |
|---|---|---|---|
| **Sampling rate** | 60 fps | 50 fps | Up to 100 fps |
| **Body points** | 29 skeletal | 21 skeletal | 29 skeletal / 10,000 mesh |
| **3D tracking** | Yes | Yes | Yes |
| **Players tracked** | 10 | 22 | 22 |
| **Environment** | Indoor | Outdoor | Outdoor |

**Fig. 2.** Football's top leagues already capture skeletal data at resolution comparable to — and in some cases exceeding — the NBA's system. No football league has built consumer-facing analytical products on top of it. Sources: Genius Sports [11], DFL/TRACAB [12], Hawk-Eye [13], NBA/Hawk-Eye [14].

The comparison with basketball is instructive — but not in the direction commonly assumed. The NBA's Hawk-Eye installation, deployed across all 30 arenas from the 2023–24 season, captures 29 skeletal points per player at 60 fps [14]. The Premier League's system captures the same number of skeletal points at a higher frame rate. Football's top leagues are already collecting body-pose data at resolution comparable to — and in some cases exceeding — what the NBA provides.

The divergence is entirely in what is built on top of this data. In October 2025, the NBA launched three new public-facing statistics explicitly derived from pose tracking: `Gravity` (quantifying defensive attention and space creation), `Shot Difficulty` (analysing how stance and mechanics affect accuracy), and `Defensive Box Score` (attributing defensive impact in real time) [15]. Football has no equivalent. The skeletal data that could support biomechanical assessment of shooting mechanics, dribbling posture, tackling form, and running gait is collected every matchday in the Premier League and Bundesliga. It is consumed for officiating and tactical analysis. It is not consumed for the mechanical assessment that this publication argues is the missing variable in transfer prediction.

The Sport Performance Lab (SPL) at Maple Leaf Sports & Entertainment — parent company of the Toronto Raptors, Toronto FC, and the Toronto Maple Leafs — demonstrates what the downstream application looks like. The SPL employs a dedicated biomechanics data scientist whose role involves analysing "player body pose data" to "gain competitive advantages that best inform front office staff of player movement behaviours" [16]. The front office inclusion is the critical detail. This is biomechanics integrated into the player evaluation and acquisition process.

The Raptors' Shooting Lab — which won the 2026 NBA Team Innovation Award — uses the same underlying technology to capture 29 body points at 60 fps and analyse elbow velocity, release angle, stance width, and shot trajectory [17]. In November 2025, the NBA launched a league-wide biomechanics assessment programme: standardised motion capture labs at all 30 team facilities, over `500+` players assessed, using Qualisys, Theia Markerless, Bertec, and BreakAway Data, with P3 as consultant [18]. MLSE's SPL-Open-Data initiative has open-sourced markerless motion capture datasets to build the analytical community [19], and the SPLxUTSPAN Data Challenge on Kaggle invites researchers to predict free throw outcomes from biomechanical data [20].

Devin Pleuler, the Senior Director of R&D for Team Operations at MLSE and leader of the SPL, has observed at a research conference that with the expanded tracking data now available, the competitive moat has shifted. The moat is no longer the data — it is the physicists and biomechanists who can derive new insight from it.

> *Pleuler's career illustrates the cross-sport trajectory: he worked for Opta and Major League Soccer before joining MLSE, where the multi-sport structure — Raptors, Toronto FC, Maple Leafs, Argonauts — creates conditions for cross-pollination between analytics, sports science, and biomechanics that single-sport football clubs typically lack.*

His observation maps precisely to the structural argument of this publication. The cost of collecting biomechanical data in football has already been paid — the cameras are in the stadiums, the skeletal tracking is operational, the data is generated every matchday. What has not been built is the analytical layer that converts skeletal data into mechanical assessment: the framework that asks whether a player's execution quality predicts success in the target environment.

Sony's recent acquisitions sharpen the picture. Between October 2024 and October 2025, Sony acquired KinaTrax (markerless biomechanical motion capture, deployed in 75+ MLB stadiums) and STATSports (wearable GPS tracking, used by 800+ football clubs) to complement Hawk-Eye, which already provides skeletal tracking across 23 of the top 25 global sports leagues [21]. The company now owns every component required to build a biomechanical scouting product for football: optical skeletal capture, validated biomechanical analysis, and wearable physical data. Whether it will is an open question. That the components exist and are commercially assembled under a single corporate entity is a fact.

07

## Why the Gap Persists

*Paradigmatic, not technical*

If football's data infrastructure already captures skeletal data at the resolution required for biomechanical assessment, why has no one built the analytical products?

The answer is paradigmatic, not technical.

Football's analytics community was built by mathematicians, computer scientists, and data scientists who professionalised the field through event data modelling. The intellectual heritage is statistical: expected goals, passing networks, possession value models. Biomechanics — the science of human movement — is a separate disciplinary tradition with different methods, different training, and different institutional homes. The football analytics community and the sports biomechanics community have developed largely in parallel, with minimal integration. The people who build the models and the people who understand human movement operate in different departments, report to different directors, and attend different conferences.

The NBA's advantage is organisational. MLSE's Sport Performance Lab sits across all their teams, integrating analytics, sports science, and biomechanics into a single research function with shared infrastructure and a common rapid-prototyping platform [22]. Football's typical organisational structure separates the data department (which does player evaluation) from the sports science department (which does physical assessment and injury prevention). The biomechanical expertise exists within football clubs — in the medical and sports science staff — but it is not integrated into the scouting and evaluation pipeline.

The DFL's Automated Event Detection system, which entered operational trials in the Bundesliga at the start of the 2025–26 season, represents the first attempt to build analytical products on top of skeletal tracking data in football [12]. Currently it detects on-ball events (passes, shots, set pieces) automatically from skeletal data. Off-ball event detection — including body-part identification and body orientation — is under development. This is a step toward biomechanical analytics, but it remains oriented toward event classification rather than execution quality assessment.

> The clubs that bridge the organisational gap — making biomechanical assessment an input to player evaluation, not just a tool for injury prevention or officiating — gain access to a predictive variable that their competitors' models structurally exclude. The advantage is paradigmatic, not incremental. And for the first time, it does not require new data collection infrastructure. The data is already there.

08

## What the Standard Metrics Collapse

*Mechanical decompositions across five dimensions*

Each mechanical dimension below decomposes an action that event data records as a single unit. In every case, the decomposition reveals information that the collapsed measurement destroys — information directly relevant to whether a player's capability will transfer to a new environment.

### Striking: Why xG Cannot Predict Finishing Transfer

Expected goals measures the probability that a shot taken from a given location, in a given game state, results in a goal. It captures the situation. It does not capture how the body produced the shot. The kinetic chain involved in a football strike — hip generating the greatest moment, knee reaching maximum force at full extension, ankle applying spin and trajectory control [23] — produces measurable differences in execution quality. A compact release (short backlift, rapid contact) predicts the ability to shoot effectively under defensive pressure: the snap release that produces a goal in tight spaces in the Portuguese league will produce comparable goals in the Premier League, because the mechanical profile is suited to compressed time and space. A wide release (long backlift, full wind-up) predicts power in open situations but vulnerability to fast-closing defenders. xG treats both shots identically if they originate from the same location.

Shot preparation — the pre-execution sequence of creating separation from a marker, taking a directional set touch against the defender's momentum, and establishing an open stance for the strike — is itself a mechanical skill distinct from the shot. The player who can manufacture shooting angles through separation mechanics possesses a capability invisible to xG, which measures the shot location but not the mechanical process that created the opportunity. Football analytics has measured receptions and it has measured shooting. The unmeasured middle — how players manufacture the angle between receiving the ball and striking it — is a mechanical dimension with direct implications for how goal-scoring ability transfers between environments [24].

### Dribbling: Why Carry Statistics Mislead

A "successful dribble" in event data is a binary outcome: the player advanced the ball past a defender, or they did not. This collapses three distinct phases — each with different mechanical demands — into a single result [25].

The **preparation phase** determines the range of available attack options: the player's orientation when receiving, their spatial relationship with defenders, the momentum they carry into the contest. The **reception phase** sets the foundation: first-touch direction, posture, ball proximity. The **attack phase** determines the outcome: direction changes, acceleration, feints, stride control. A player can be elite in one phase and limited in another — and the limitation is invisible in the collapsed statistic.

Manchester United's Alejandro Garnacho provides a case in point. He ranks in the `99th percentile` for carries into the penalty area and the `93rd` for progressive carries — elite at advancing the ball over distance. He sits in the `5th percentile` for take-on success rate, despite attempting `5.71` take-ons per 90 (`85th percentile`) [25]. The carry statistics say world-class dribbler. The take-on statistics say the opposite. The mechanical analysis identifies where the discrepancy originates: his take-on mechanics resemble a template built for a different physical profile — more explosive in short bursts, faster from a standing start. The preparation and reception phases are strong; the attack phase encounters a mismatch between mechanical template and physical substrate.

Van Haaren et al.'s analysis of 1,736 dribbles confirms that the mechanical dimension carries predictive information the event record destroys. Attacker lean angle, defender body posture, and the relative spatial alignment between the two players at the moment of engagement — all skeletal-data variables, invisible to event tagging — were among the strongest predictors of dribble success [10].

The broader concept at work is **techno-physical capacity** — the interaction between a player's physical build and their technical execution range. Every athlete's physical structure determines a range of feasible motion. Intersecting that range with their trained perception-action patterns yields the set of actions they can consistently execute under competitive pressure. Scouting that evaluates technique without reference to the physical context in which it operates is evaluating a different variable than the one that determines performance in the target environment.

### Defending: Why Tackle Statistics Produce Opposite Predictions

The defensive case was introduced in Section 5, but its analytical implication extends further. The standard tackle metric records an outcome: the ball was won or it was not. The mechanical assessment asks three questions the outcome alone cannot answer: From which angles and at what proximity can the player effectively contest? What happens post-tackle — is the ball retained, loose, or out of play? And what physical and mental exertion does the action require [7]?

These questions produce system-fit predictions that tackle statistics cannot. A player whose tackling mechanics are sprint-intensive will excel in a high-line system and struggle in a low-block. A player whose tackling mechanics allow ground-level challenges from multiple angles will excel in pressing traps and disruptive schemes. The tackle completion rate may be identical. The mechanical profile — and therefore the system-fit prediction — is entirely different.

### Running: Why Distance Covered Is Structurally Incomplete

Tracking data captures distance covered per 90, sprint counts, and top speed. These are action-level measures of running. They do not capture purpose, sustainability, or contest readiness at the end of a run.

Running capacity decomposes into at least four tiers [26]: players who cannot sustain high-intensity sprinting across a match; players who can sprint but without covering purpose; players who run and cover, combining physical output with positional intelligence; and players who run, cover, and maintain aggression into subsequent duels. Modern pressing systems have made the highest tier a premium asset. Liverpool manager Arne Slot, after his side's 3-0 victory over Manchester United in September 2025, stated the requirement directly:

> *"You need midfielders that can run. We had three of them that kept on running and, if they arrived in a duel, they were aggressive enough to win it."*
>
> Arne Slot, post-match, Liverpool 3-0 Manchester United, September 2025 [26]

This capacity is mechanical: it depends on stride efficiency, energy management, deceleration patterns, and the neuromuscular ability to transition from running to contesting without degradation. A player's `11.5km` per 90 may represent purposeless running or aggressive covering. The number is the same. The transfer prediction is not.

### Spatial Control: The Contest Primitive

Across dribbling, tackling, aerial duels, and physical contests, a single mechanical concept recurs: the zone of spatial control around a player's centre of gravity, within which they can effectively manipulate the ball and resist encroachment [27]. The stiff arm — deployed across football, basketball, rugby, and American football — is a mechanical tool for expanding this zone. Players who wield it as a trained pattern possess a duel advantage that statistics capture as an outcome but not as a mechanism. The aerial contest dimension, examined in our prior research (SW-R-2026-001), similarly identifies the pre-contact phase as analytically significant — positioning and timing decisions that are mechanical, not tactical, and that the standard aerial duel metric structurally excludes [28].

> The standard metrics record what happened. Mechanical assessment identifies the physical process that determined the outcome — and it is the physical process, not the recorded outcome, that predicts whether the capability transfers to a new environment.

METHODOLOGY NOTE

This publication synthesises three categories of evidence. The market data — transfer spending, goal records, performance timelines — is drawn from publicly reported figures and constitutes empirical observation. The cross-domain and infrastructure evidence — the NBA's biomechanical analytics, MLSE's Sport Performance Lab, football's skeletal tracking infrastructure, and the Van Haaren et al. dribbling study — is documented through official announcements, academic publications, and institutional communications; it constitutes verified operational and empirical precedent. The structural argument — that mechanics is the most context-independent layer of player performance and therefore the strongest predictor of skill transfer — is a well-grounded inference supported by the cross-domain precedent, the Van Haaren findings, and the logical structure of the compounding stack, but not yet validated by a controlled transfer-outcome study in football. We do not claim that the transfer market's failures are entirely attributable to the absence of mechanical assessment. Graham's research identifies seven distinct reasons why transfers fail, of which mechanical mismatch is one [30]. We claim that mechanical assessment addresses a structural gap in the analytical pipeline that no amount of improvement to action-level metrics will close.

No controlled study currently exists that isolates mechanical profile as a predictive variable for transfer outcomes in football. The case evidence from the 2025–26 season is illustrative, not definitive. What this publication establishes is the structural case: that the variable the transfer market is missing is identifiable, assessable with data already being collected, and — based on structural reasoning, cross-domain precedent, and emerging empirical evidence — predictive. The empirical validation is the next step. A companion proof-of-concept [31] tests whether body-pose features derived from the kinetic chain framework carry identifiable signal for shot outcome prediction; its results, limitations, and next steps are reported separately.

DATA SOURCES AND REPRODUCIBILITY

The transfer spending figures and player performance data are drawn from publicly available sources (ESPN, FOX Sports, Sky Sports, Transfermarkt) and are independently verifiable. The infrastructure data is drawn from official provider announcements (Genius Sports, TRACAB/DFL, Hawk-Eye, NBA), AWS case studies, and publicly accessible role descriptions. The Van Haaren et al. dribbling study is available on arXiv. The structural argument derives from STATSWING's prior research (SW-R-2026-001, SW-R-2026-002). The mechanical dimension decompositions draw on STATSWING's published analytical work. Specific dimensional scoring protocols and integration methodology are proprietary and not disclosed.

TRANSFER PREDICTION | BIOMECHANICS | EXECUTION QUALITY | SKELETAL TRACKING | COMPOUNDING STACK | SCOUTING METHODOLOGY

## IMPLICATIONS BY AUDIENCE

### For Clubs

The transfer market's failure rate — approximately **46%** by Graham's generous measure [6] — represents an enormous and recurring cost. A proportion of that failure derives from the absence of mechanical assessment in the scouting process. Clubs that integrate biomechanical evaluation into their recruitment gain a structural advantage: the ability to predict transfer outcomes on a variable that their competitors' models do not include.

The practical recommendation is direct: before committing investment to a player identified through statistical scouting, commission a mechanical assessment that answers two questions. First, does the player's execution quality in the key mechanical dimensions match the demands of the target system? Second, are the aspects of the player's statistical profile that are most valuable in the current environment produced by mechanical qualities that are portable, or by contextual factors that will not persist?

The NBA provides the institutional precedent. The Raptors did not wait for the league-wide biomechanics programme — they built the capability years before it was mandated, accumulating data, expertise, and integrated workflows that now compound with each season. The football club that follows this model gains the same first-mover advantage. Critically, Premier League and Bundesliga clubs already receive the skeletal tracking data that makes this possible. The investment required is not in data infrastructure — it is in the analytical expertise and organisational integration to use data that is already being collected.

### For the Football Analytics Community

The next phase of football analytics requires a disciplinary expansion. Biomechanics is not a refinement of the statistical toolkit; it is a different field with different methods. The integration requires either hiring from that field (as the Raptors hired a biomechanics data scientist with a kinesiology degree) or building collaborative structures that bring biomechanical expertise into analytical workflows. MLSE's Sport Performance Lab — a research function that sits across teams, integrates analytics, sports science, and biomechanics, and shares infrastructure through a common platform — is an organisational model worth studying.

### For Data Providers

The space between physical data (speed, distance, acceleration) and event data (passes, shots, goals) is commercially unoccupied by any provider offering biomechanical execution quality metrics for football. The provider that arrives first with such a product occupies the same position StatsBomb occupied when it introduced 360 freeze-frame data: not a marginal improvement to the existing product category, but a categorical expansion of what the market can see. Sony's vertical integration — Hawk-Eye (skeletal tracking), KinaTrax (biomechanical analysis), STATSports (wearable data) — suggests that the components for such a product are commercially assembled. Whether an integrated biomechanical scouting product emerges from that portfolio is among the most consequential developments to watch in sports data.

### For Coaches

If mechanical quality is the primary determinant of skill transfer, then coaching that targets mechanics — not just tactical instruction or confidence management — is the most effective intervention when a new signing is struggling. A coaching staff that identifies a new signing's adaptation problem as mechanical (reception body shape incompatible with the pressing tempo) will design different training interventions than one that identifies it as tactical (doesn't understand the pressing triggers) or psychological (hasn't settled). The developmental sequence described by practitioners — establish range of motion through corrective exercises, train movement skills to use that range effectively, then apply in context [29] — is a structured approach to mechanical intervention. It is the opposite of the "give them time" default, which assumes that the adaptation problem is one of familiarity rather than physical execution. Some adaptation problems are familiarity. Some are mechanical. The distinction determines whether time resolves them.

## REFERENCES


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## CITE THIS PUBLICATION

J. Adejola, "The Execution Layer: Mechanics as the Missing Variable in Transfer Prediction," STATSWING Research SW-R-2026-003, March 2026. statswing.com/research/mechanics/

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SW-R-2026-003