REVIEW ARTICLE

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From Discovery to Decision Impact in Precision Sports Medicine: A Review-Level Translational Evidence Map

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Abstract: Precision sports medicine now integrates genetic, molecular, wearable, imaging, biomechanical, and artificial intelligence data. However, it is still unclear how strong the evidence must be to inform judgments about athlete management. Using PubMed, Scopus, and Web of Science across six predetermined categories, this study created a structured review-level translational evidence map. Of the 7,147 unique records that underwent title and abstract screening after deduplication, 944 were retained as potentially eligible. Athlete relevance, precision-domain fit, complementarity, recency, domain coverage, and redundancy management were then used to prioritize a prespecified principal corpus of 75 peer-reviewed systematic reviews and meta-analyses. These 75 reviews do not represent the entire set of eligible reviews. The corpus was finalized by a single author/reviewer who applied predefined review-level grades for translational maturity, consistency, replication, evidentiary confidence, and decision/clinical utility. In the prioritized corpus, 11 reviews attained R2, 21 reached C2, 1 reached EC3, and 11 reached T3. 74 of 75 remained at CU0-CU1, and none made it to T4-T5. Certain wearable, imaging, and neuromuscular applications produced the strongest validation signals. Where biomarker specificity, candidate-gene heterogeneity, calibration, and external transportability were uncertain, translation was weaker. Sensitivity analyses restricted to recent, methods-rich, and meta-analytic reviews yielded the same general conclusion. Evidence of demonstrated decision impact has not advanced as quickly as measurement and prediction. Thus, independent replication, intended-use-specific validation, calibration, incremental value, and potential athlete-management outcomes should be given more weight in future research.

Keywords: Precision Sports Medicine, Biomarkers, Multi-Omics, Wearables, Biomechanics, Artificial Intelligence, Injury Prediction, Athlete Monitoring, Translational Medicine.

1. Introduction

Precision sports medicine extends the principles of personalized care to the athlete context. Decisions in this context must account for changing physiology, training exposure, competitive demands, injury status, rehabilitation, and performance goals. Genetic variants may indicate inherited predisposition. Molecular biomarkers can reflect tissue stress, inflammation, neurological damage, or energy status. Wearable technology provides repeated physiological and exposure measurements. Tissue and movement phenotypes are characterized by imaging and biomechanical testing, and high-dimensional signals can be combined using machine-learning techniques. These approaches have considerable scientific promise. A statistically linked marker, however, does not satisfy the evidentiary standard necessary for precision sports medicine practice on its own. This distinction is evident in recent evaluations of sports science. Recent concussion reviews suggest that fluid biomarkers and neuroimaging may identify physiological alterations that persist after clinical symptoms resolve, but current evidence is insufficient to support routine clinical use (Tabor *et al.,* 2023). Reviews of wearable sensors, training-load monitoring, and fatigue biomarkers report recurring associations with athlete status. Simultaneously, they find significant differences in outcome definitions, analytical techniques, devices, and sampling schedules (Soler-López *et al.,* 2024; Clemente *et al.,* 2025; Crang *et al.,* 2021). Therefore, biological

responsiveness does not guarantee a marker's specificity, calibration, or actionability for an individual athlete.

This distinction is equally important for artificial intelligence. Although injury-risk and return-to-sport models can show useful discrimination, insufficient sample sizes, data leakage, inappropriate partitioning, a lack of external validation, and inadequate calibration reporting can distort their reported performance (Aslani *et al.,* 2026; Bullock *et al.,* 2022; Satija and Dkhar, 2026; Lou *et al.,* 2026). Even if a model performs well statistically, it does not necessarily improve athlete care. Evidence that the model improves a meaningful athlete or organizational outcome, influences a relevant decision, functions safely and fairly, and offers information beyond current practice is necessary for translation. The majority of reviews that are currently available focus on a single technology, marker class, sport, or specific outcome.

Few use the same translational criteria to compare wearables, genomics, molecular biomarkers, imaging/biomechanics, and AI. Fewer still distinguish between decision value and a quantifiable association. Instead of creating a separate technology catalog, this structured review-level evidence map fills that gap by comparing six evidence categories using a single translational framework. The analysis was guided by four questions: what evidence structure is required for responsible multimodal precision sports medicine; which markers, measurements, or models demonstrate athlete-management or clinical utility; which methodological obstacles prevent progression from prediction to prospective decision impact; and which precision-sports domains have advanced from discovery to independent replication or validation.

2. Methods

2.1 Design and Protocol

The study was designed as a structured review-level translational evidence map. An internal a priori protocol specified the review questions, six evidence domains, eligibility rules, deduplication hierarchy, screening logic, principal-corpus prioritization rules and R/C/EC/T/CU grading scales before the final 75-review corpus was graded. The protocol was not externally registered. PRISMA 2020 (Page *et al.,* 2021) informed reporting of record identification and screening. The study was not designed as an exhaustive systematic overview of all eligible reviews; rather, it characterizes a predefined prioritized review corpus assembled for cross-domain translational comparison.

2.2 Information Sources and Search Domains

Search results from PubMed, Scopus and Web of Science were combined. PubMed and Web of Science searches were completed on 10 August 2026, and the Scopus search on 11 August 2026. Six domains were defined in advance: genomics and epigenomics (GEN); molecular omics and circulating biomarkers (MOL); digital biomarkers and wearables (DIG); imaging, biomechanics and neuromuscular markers (IMG); artificial intelligence and multimodal integration (AI); and explicit precision sports medicine terminology (PSM). Searches covered database inception to the respective search date. Review-level filters or terms were applied with no restrictions on language, free-full-text availability, publication year, adult populations or elite athletes. Supplementary Table S1 gives the database-specific search syntax. Where an archival search file contained named query blocks rather than a fully expanded search string, S1 expands the preserved block definitions without altering the underlying concepts.

2.3 Eligibility and Screening

Records were deduplicated in a hierarchical sequence using normalized DOI, PMID, normalized exact title, title-author-year matching and fuzzy-title review for uncertain cases. This process produced 7,147 unique records. Title and abstract screening followed a conservative rule: records were retained when the available information was insufficient for confident exclusion. Eligibility for the principal review corpus required an athlete or sport population, a substantive precision-data domain, an athlete-relevant outcome, and a systematic-review or meta-analytic design. Mixed-population reviews were retained only when athlete-specific findings could be extracted separately or when athlete data clearly dominated the evidence base.

Reviews focused mainly on training, treatment or supplementation effects were not prioritized unless they also examined a relevant marker, model or measurement domain. Scoping and narrative reviews were used for context where needed, but they were not treated as independent principal evidence. Screening retained 944 potentially eligible records and excluded 6,203. These 944 records formed the candidate pool for evidence-map prioritization.

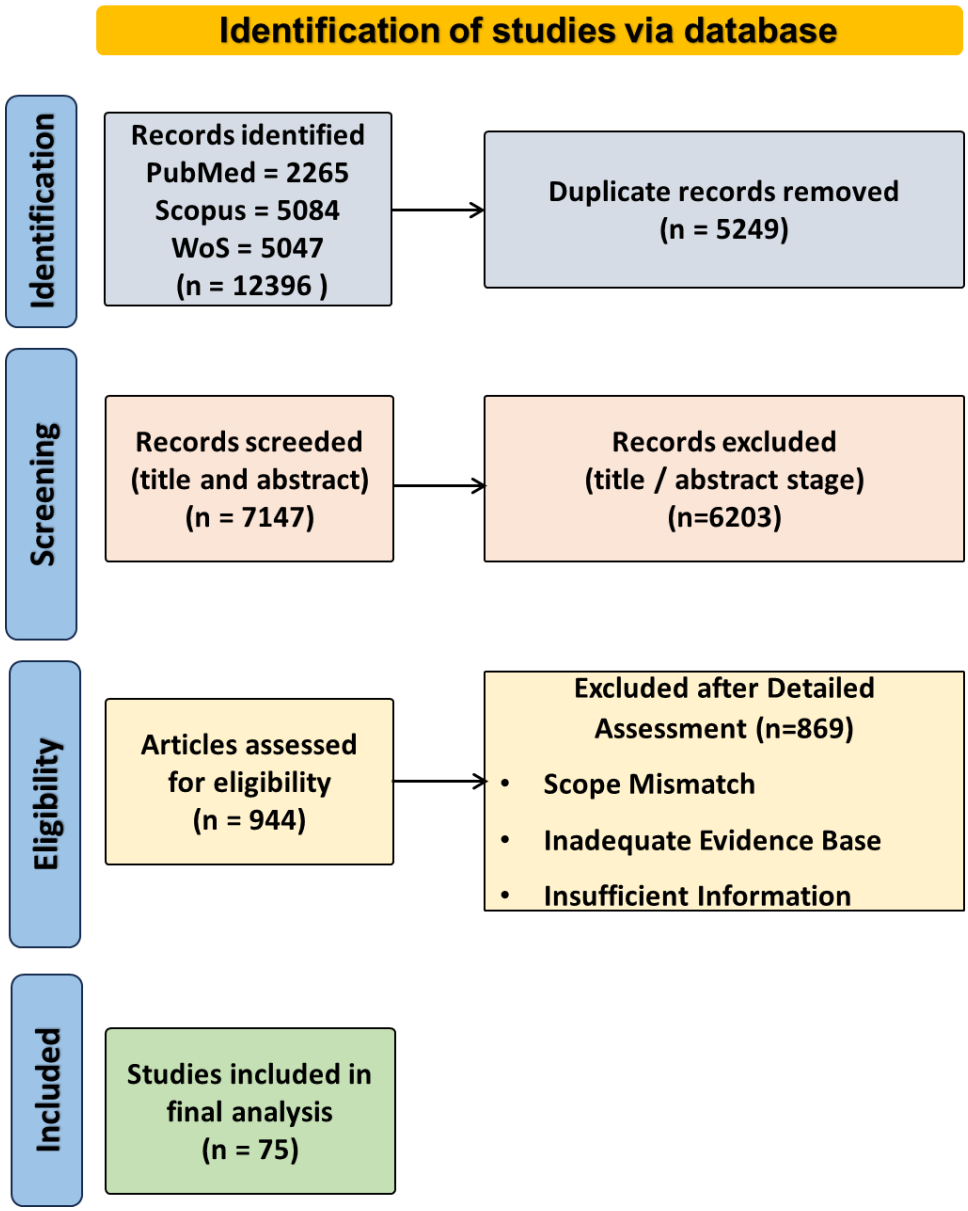

Figure 1. Evidence identification and principal-corpus construction.

They were not treated as a conventional full-text inclusion set. Figure 1 presents the PRISMA 2020-style identification and prioritization flow. All maturity counts and proportions reported in this manuscript refer only to the prioritized 75-review principal corpus.

2.4 Principal-Corpus Construction and Redundancy Management

Principal-corpus construction separated broad title and abstract eligibility from evidence-map prioritization. Reviews were prioritized when they directly addressed an athlete population, one of the prespecified precision-data domains and an athlete-relevant outcome, and when they contributed distinct evidence to at least one review question. When reviews overlapped substantially in population, marker or exposure, and outcome, priority was given to the more recent and comprehensive review. An earlier review was retained when it added a distinct population, sport, marker class, outcome, validation question or methodological perspective. The final 75-review corpus was therefore selected to maximize translational coverage rather than to represent the 944 potentially eligible records statistically. Supplementary Table S2 provides a record-level disposition for all 944 records: 75 entered the principal corpus, 32 were classified as redundant or overlapping, 2 as superseded, 42 as contextual, 16 as having insufficient information for principal-corpus prioritization, and 777 as having a narrower or more peripheral scope relative to the main translational questions. These categories describe

evidence-map prioritization and should not be read as conventional full-text exclusion categories.

2.5 Review-Level Methodological Appraisal

At the review level, methodological evaluation was restricted to protections that could be confirmed by the available evidence. Protocol or registration status, duplicate review processes, risk-of-bias evaluation of primary research, publication-bias evaluation when applicable, and other design-specific methodological aspects were among the items that were extracted. Evidence-access tiers were not utilized as quality evaluations; instead, they represented the amount of source material available. The descriptive appraisal was informed by AMSTAR 2 and design-specific issues (Shea *et al.,* 2017; Wolff *et al.,* 2019). When item-level data could not be confirmed, no composite score was given. This evaluation was carried out by the same author/reviewer who completed the 75-review corpus.

2.6 Primary-Study Overlap

Reviews were organized into thematic overlap clusters. Corrected covered area (CCA) is an established method for measuring overlap (Pieper *et al.,* 2014), but its calculation requires a complete review-by-primary-study citation matrix. Reference lists and cited-study information were examined when available. Complete primary-study lists could not be recovered for every review in each cluster, so numerical CCA was not calculated. Overlap was instead managed by prioritizing broader or newer reviews when they subsumed earlier evidence questions. Replication was also graded conservatively so that repeated use of the same primary cohorts across publications was not counted as independent replication. Supplementary Table S5a presents the final cluster-level overlap map.

2.7 Evidence Extraction

The extraction matrix recorded bibliographic data, review design, the number of included primary studies and participants when stated explicitly, athlete population, marker or model, intended use, outcome, methodological safeguards, overlap cluster, external validation, calibration, representation, and important limitations for each principal review. The manuscript reference list and retrievable source records were then checked against the locked master dataset in a thorough data-validation audit. Corrections were made to values that represented search yields, eligibility requirements, or subgroup counts instead of actual included-study or participant totals. When a trustworthy value could not be determined, the field was reported as NR rather than inferred. The validated review characteristics are listed in Supplementary Table S3.

2.8 Translational Grading Framework

Five complementary dimensions were defined before final grading: replication (R0-R4), consistency (C0-C4), review-level evidence confidence (EC1-EC4), translational maturity (T1-T5), and decision/clinical utility (CU0-CU4). Table 1 lists Operational definitions of the review-level grading framework. These dimensions are related but not strictly hierarchical, and they are not presented as a validated consensus instrument. The EC scale was developed for this review and is not equivalent to formal GRADE. For T3 evidence, validation was further classified by intended use as analytical or measurement validity, clinical or diagnostic validity, or predictive or prognostic validation. Internal resampling and cross-validation were not counted as external validation. Temporal, cross-team, geographical, cross-sport and cross-platform transportability were recorded separately. When evidence fell between two grades, the lower clearly supported category was assigned.

2.9 Grading Procedure and Reviewer

One author evaluated all 75 principal reviews and assigned the R/C/EC/T/CU classifications using the predefined decision manual. A second independent grader was not used, so inter-rater agreement was not calculated. Borderline or internally inconsistent cases were checked again against the extraction record and available source documentation. When uncertainty remained, the lower category was retained. These grades describe review-level evidence. They should not be interpreted as counts of independent technologies, biomarkers or primary evidence bodies. Supplementary Table S4 provides full traceability for the grading and validation subtypes.

2.10 Synthesis and Sensitivity Analyses

Domain summaries were generated directly from the S4 grading dataset. Sensitivity analyses repeated the summary for methods-rich reviews, methods-rich reviews plus reviews with substantive methodological signals, reviews published from 2020 onward, and reviews containing a meta-analysis.

Table 1. Operational definitions of the review-level grading framework

Dimension	Grade	Operational definition
Replication	R0	Replication cannot be assessed or was not evaluated.
Replication	R1	More than one report or study is available, but independence is uncertain, findings are inconsistent, or replication cannot be demonstrated.
Replication	R2	The signal is supported by at least two demonstrably independent athlete cohorts or populations, or by independent primary studies within the review evidence.
Replication	R3	Replication is shown across at least three independent populations, sports or settings, with limited dependence on one cohort.
Replication	R4	Broad replication is shown across independent populations, sports or settings and participant groups, supporting generalizability.
Consistency	C0	Consistency cannot be assessed.
Consistency	C1	Findings are mixed, heterogeneous or conflicting across studies or subgroups.
Consistency	C2	Most studies show a similar direction of effect, although residual heterogeneity or contextual dependence remains.
Consistency	C3	Findings are consistent across several independent populations or settings, with limited important heterogeneity.
Consistency	C4	Findings are highly consistent across diverse sports, settings and participant groups.
Evidence confidence	EC1	Very low confidence: evidence is sparse, indirect, methodologically weak, highly heterogeneous or incompletely verifiable.
Evidence confidence	EC2	Low confidence: several data points are available, but important limitations in quality, consistency, directness or validation remain.
Evidence confidence	EC3	Moderate review-level confidence: review methods are comparatively strong, evidence is direct and consistent, and no dominant unresolved limitation is evident.
Evidence confidence	EC4	High review-level confidence: evidence is broad, direct and methodologically strong, with independent validation and little major uncertainty.
Translational maturity	T1	Discovery or exploratory association.
Translational maturity	T2	Replicated association, model development or evidence synthesis without adequate independent or criterion validation.
Translational maturity	T3	Measurement, diagnostic or predictive validity is demonstrated against an appropriate criterion or independent validation framework.
Translational maturity	T4	Incremental utility or decision impact is demonstrated in a prospective or real-practice decision pathway.
Translational maturity	T5	Prospective implementation shows that marker- or model-guided management improves meaningful athlete outcomes with acceptable level of burden and harms.
Decision/clinical utility	CU0	Clinical or athlete-management utility was not evaluated.
Decision/clinical utility	CU1	Potential monitoring or decision utility is proposed but not directly evaluated.
Decision/clinical utility	CU2	Decision impact or clinically relevant decision-support performance is evaluated.
Decision/clinical utility	CU3	Use of the marker or model is shown to change athlete management in practice.
Decision/clinical utility	CU4	Prospective athlete-outcome benefit is demonstrated from marker- or model-guided management.

These analyses were descriptive safeguards against dependence of the main interpretation on evidence-access level, recency or review design; no inferential population estimate was intended. Domain and sensitivity summaries are provided in Supplementary Table S5b.

3. Results

3.1 Evidence Identification and Corpus Characteristics

The prioritized principal corpus included 75 peer-reviewed reviews published from 2012 to 2026, with a median publication year of 2024. Sixty-three reviews (84.0%) were published from 2020 onward, and 40 (53.3%) from 2024 onward. The corpus contained 7 cross-domain or precision reviews, 11 genomics or epigenomics reviews, 13 molecular biomarker or omics reviews, 15 digital biomarker or wearable reviews, 20 imaging, biomechanics or neuromuscular reviews, and 9 AI or multimodal reviews. Supplementary Table S3 provides the validated study characteristics. Fourteen reviews were classified as methods-rich, 42 had abstract or metadata information together with methodological signals, and 19 were supported mainly by abstract or bibliographic information. These categories indicate information availability only. The corpus also included cross-domain work on multimodal AI, neuroimaging and precision integration (Wang *et al.,* 2026; Gkintoni *et al.,* 2026).

3.2 Overall Translational Maturity

The main pattern in the 75-review principal corpus was clear: the volume of published evidence was much greater than its translational maturity. Replication was graded R0 in 54 reviews, R1 in 10 and R2 in 11; no review reached R3-R4. Consistency was C0 in 23 reviews, C1 in 31 and C2 in 21. Evidence confidence was EC1 in 44 reviews, EC2 in 30 and EC3 in one; none reached EC4. Translational maturity was T1 in 21 reviews, T2 in 43 and T3 in 11; none reached T4-T5. Decision or clinical utility was CU0 in 50 reviews, CU1 in 24 and CU2 in one; no review reached CU3-CU4. These figures describe the prioritized corpus and should not be interpreted as prevalence estimates for all potentially eligible reviews. The only EC3 review was the systematic review and meta-analysis of sleep quality, training load and musculoskeletal injury risk in adolescent athletes (Sihanto and Hakiki, 2026). The only CU2 review assessed biomechanical tools for injury-risk prediction and return-to-sport decision support (Alahaidib *et al.,* 2025). The 11 T3 reviews reflected different forms of validation, including analytical or measurement validity, clinical or diagnostic validity, and predictive or prognostic validation. These subtypes are reported in Supplementary Table S4. The 11 R2 reviews are also traceable in S4 (Tabor *et al.,* 2023; Clemente *et al.,* 2025; İpekoğlu *et al.,* 2024; Ferreira *et al.,* 2024; Greenham *et al.,* 2018; Lindsey *et al.,* 2025; Hollander *et al.,* 2019; Kumar *et al.,* 2024; Yan *et al.,* 2025; Heming *et al.,* 2025; Paravlic, 2025). The five dimensions were designed to capture different aspects of maturity rather than a single hierarchy. A wearable device, for example, may show criterion validity without a replicated association with athlete outcomes. A prediction model may show internally validated discrimination but still lack external transportability. T3 therefore indicates a specific validation step for the intended use, not general clinical maturity. Table 2 shows Domain-level evidence maturity in the principal review corpus.

3.2.1 Sensitivity Analyses

The translational-scarcity interpretation was unchanged in prespecified descriptive sensitivity subsets. Among methods-rich reviews (n=14), 3 reached T3+ and none reached T4-T5 or CU3-CU4. Among methods-rich reviews plus method-signal reviews (n=56), 8 reached T3+ and 1 reached CU2+. Reviews published from 2020 onward (n=63) contained 10 T3+ reviews, and reviews with a meta-analysis component (n=31) contained 3 T3+ reviews. No sensitivity subset contained T4-T5 or CU3-CU4 evidence (Supplementary Table S5b).

3.3 Genomics and Epigenomics

The genomics literature in the corpus was shaped largely by candidate-gene and polymorphism reviews of endurance, power, combat-sport performance and elite-athlete status (İpekoğlu *et al.,* 2024; Ferreira *et al.,* 2024; López-León *et al.,* 2016; Weyerstra *et al.,* 2018; Sarmento *et al.,* 2020; Youn *et al.,* 2021; Psatha *et al.,* 2024; Anastasiou *et al.,* 2024; Mijaica *et al.,* 2025; Akkuş *et al.,* 2026). It should not be taken as a complete picture of contemporary sports genomics. Across these reviews, reported associations varied with ancestry, phenotype definition, sport classification and analytical model. Frequently discussed variants such as ACE and ACTN3 did not support deterministic selection or exclusion of athletes. Injury susceptibility represents a different use case. An

athlete-specific meta-analysis of genetic polymorphisms linked to anterior cruciate ligament injury provided evidence of probabilistic susceptibility (Bulbul *et al.,* 2023), but it did not establish diagnostic cut-offs or management thresholds. Overall, genomics evidence remained mainly at T1-T2 and CU0-CU1.

3.4 Molecular Omics and Circulating Biomarkers

Molecular evidence varied widely in both biological target and intended use (Greenham *et al.,* 2018; Lindsey *et al.,* 2025; Lobigs *et al.,* 2018; Meyer et al., 2020; Kostelnik *et al.,* 2021; Goulart *et al.,* 2022; Khoramipour *et al.,* 2022; Walter *et al.,* 2022; Ishikawa *et al.,* 2023; e Silva *et al.,* 2024; Grainger *et al.,* 2024; Fernandes *et al.,* 2025; Guisado-Cuadrado *et al.,* 2026). Reviews of monitoring and recovery examined training stress, fatigue, post-match responses and tactical readiness (Soler-López *et al.,* 2024; Greenham *et al.,* 2018; Lindsey *et al.,* 2025; e Silva *et al.,* 2024; Grainger *et al.,* 2024; Fernandes et al., 2025). Reviews with diagnostic or injury-related aims focused mainly on fluid biomarkers in concussion (Tabor *et al.,* 2023; Meyer *et al.,* 2020; Walter *et al.,* 2022).

Table 2. Domain-level evidence maturity in the principal review corpus

Evidence domain	Reviews	R2+	C2+	EC3+	T3+	CU2+	Interpretation
Cross-domain / Precision	7	2/7 (29%)	1/7 (14%)	0/7 (0%)	0/7 (0%)	0/7 (0%)	Multimodal evidence is increasing, but most applications remain short of demonstrated utility.
Genomics / Epigenomics	11	2/11 (18%)	6/11 (55%)	0/11 (0%)	0/11 (0%)	0/11 (0%)	Candidate-polymorphism studies dominate; deterministic prediction of sporting talent is not supported.
Molecular Omics / Biomarkers	13	2/13 (15%)	4/13 (31%)	0/13 (0%)	1/13 (8%)	0/13 (0%)	Many markers respond to athlete state, but specificity and actionable thresholds remain limited.
Digital Biomarkers / Wearables	15	0/15 (0%)	3/15 (20%)	1/15 (7%)	3/15 (20%)	0/15 (0%)	Measurement validation is more advanced than replicated outcome associations or clinical utility.
Imaging / Biomechanics / Neuromuscular	20	5/20 (25%)	6/20 (30%)	0/20 (0%)	4/20 (20%)	1/20 (5%)	Validation is strongest in this domain, but it spans different diagnostic, measurement, reference-value and return-to-sport pathways.
AI / Multimodal Analytics	9	0/9 (0%)	1/9 (11%)	0/9 (0%)	3/9 (33%)	0/9 (0%)	Prediction is promising, but calibration, external validation and evidence of decision impact remain limited.

Hydration markers represented a measurement-validity use case (Kostelnik *et al.,* 2021), while hypoxia and low-energy-availability reviews addressed physiological state and athlete-health monitoring (Lobigs *et al.,* 2018; Guisado-Cuadrado *et al.,* 2026). Metabolomics and microbiome studies widened the range of candidate signals but remained affected by platform heterogeneity and high-dimensional data (Khoramipour *et al.,* 2022; Ishikawa *et al.,* 2023). Across these applications, biological responsiveness was more common than clinical specificity. A marker that changes after training,

competition or under-fuelling does not automatically identify a diagnostic, prognostic or decision-relevant state. The intensified-training synthesis found directional changes in selected markers (Greenham *et al.,* 2018), yet timing, assay platform, training phase, sex, hydration and acute illness remained important sources of variation. Concussion biomarkers may detect acute neurobiological disturbance, but validated thresholds and evidence of added clinical value are still insufficient for routine athlete management (Tabor *et al.*, 2023; Meyer *et al.,* 2020; Walter *et al.,* 2022).

3.5 Digital Biomarkers and Wearables

Wearable reviews examined inertial sensors, microsensor validity, head-impact sensing, heart-rate variability, workload monitoring, sleep, gait analysis and disability sport (Crang *et al.,* 2021; Sihanto and Hakiki, 2026; Da Silva *et al.,* 2015; Camomilla *et al.,* 2018; Patton *et al.,* 2020; Rum *et al.,* 2021; Flores *et al.,* 2023; Keys *et al.,* 2023; Cruz *et al.,* 2024; Qin *et al.,* 2025; De Sousa De Sousa *et al.,* 2025; Seifi *et al.,* 2026; Semjonova *et al.,* 2026; Hanief *et al.,* 2026). Across this literature, measurement validity consistently depended on the device, metric, sampling approach, movement pattern, algorithm and population. Evidence for one wearable-derived metric therefore cannot be assumed to apply to another device or sport. Training-load research shows why an association should not be treated as validated decision support. Studies of internal and external load and the acute:chronic workload ratio reported links with performance or injury risk, but the size and direction of these associations changed with workload definition, exposure window, mathematical specification and sport context (Clemente *et al.,* 2025; Keys *et al.,* 2023; Qin *et al.,* 2025; Hanief *et al.,* 2026; Fox *et al.,* 2018). The reviewed evidence does not support the ACWR as a universal injury-prediction threshold. Sleep measures and heart-rate variability can add useful monitoring information, but both are also affected by factors unrelated to training (Sihanto and Hakiki, 2026; Da Silva *et al.,* 2015; Flores *et al.,* 2023).

3.6 Imaging, Biomechanics and Neuromuscular Evidence

Imaging, biomechanics, and neuromuscular evidence constituted the largest domain and contained the most T3 reviews (Alahaidib *et al.,* 2025; Hollander *et al.,* 2019; Kumar *et al.,* 2024; Yan *et al.,* 2025; Heming *et al.,* 2025; Paravlic, 2025; Saki *et al.,* 2013; Schneider *et al.,* 2019; Vannatta *et al.,* 2020; Fiorese *et al.,* 2020; Esh *et al.,* 2020; Hoenig *et al.,* 2022; Kellis *et al.,* 2022; Sundaram *et al.,* 2023; Ramachandran *et al.,* 2024; Gill *et al.,* 2024; Whittaker *et al.,* 2025a; Whittaker *et al.,* 2025b; Williams *et al.,* 2025). However, rather than representing a single level of maturity, the T3 classifications reflected several types of validation. MRI diagnostic accuracy (Esh *et al.,* 2020; Hoenig *et al.,* 2022), wearable or functional measurement validity (Semjonova *et al.,* 2026), tensiomyography reference values (Paravlic, 2025), return-to-sport testing (Alahaidib *et al.,* 2025; Gill *et al.,* 2024), and biomechanical association or risk-factor evidence (Hollander *et al.,* 2019; Kumar *et al.,* 2024; Heming *et al.,* 2025; Saki *et al.,* 2013; Vannatta *et al.,* 2020; Kellis *et al.,* 2022; Sundaram *et al.,* 2023; Ramachandran *et* al., 2024; Whittaker *et al.,* 2025a; Whittaker *et al.,* 2025b; Williams *et al.,* 2025) were among them. Imaging, biomechanics, and neuromuscular evidence constituted the largest domain and contained the most T3 reviews (Alahaidib *et al.,* 2025; Hollander *et al.,* 2019; Kumar *et al.,* 2024; Yan *et al.,* 2025; Heming *et al.,* 2025; Paravlic, 2025; Saki *et al.,* 2013; Schneider *et al.,* 2019; Vannatta *et al.,* 2020; Fiorese *et al.,* 2020; Esh *et al.,* 2020; Hoenig *et al.,* 2022; Kellis *et al.,* 2022; Sundaram *et al.,* 2023; Ramachandran *et al.,* 2024; Gill *et al.,* 2024; Whittaker *et al.,* 2025a; Whittaker *et al.,* 2025b; Williams *et al.,* 2025).

However, rather than representing a single level of maturity, the T3 classifications reflected several types of validation. MRI diagnostic accuracy (Esh *et al.,* 2020; Hoenig *et al.,* 2022), wearable or functional measurement validity (Semjonova *et al.,* 2026), tensiomyography reference values (Paravlic, 2025), return-to-sport testing (Alahaidib *et al.,* 2025; Gill *et al.,* 2024), and biomechanical association or risk-factor evidence (Hollander *et al.,* 2019; Kumar *et al.,* 2024; Heming *et al.,* 2025; Saki *et al.,* 2013; Vannatta *et al.,* 2020; Kellis *et al.,* 2022; Sundaram *et al.,* 2023; Ramachandran *et al.,* 2024; Whittaker *et al.,* 2025a; Whittaker *et al.,* 2025b; Williams *et al.,* 2025) were among them. Earlier sport-specific biomechanical and physiological syntheses, including equestrian findings, were retained when they contributed a distinct athlete context (Douglas *et al.,* 2012). The intended application and study population continued to determine generalizability. The injury markers associated with running varied depending on the features of the sample (Vannatta *et al.,* 2020). Maturation, sex, and neuromuscular setting all affected ACL results (Saki *et al.,* 2013; Ramachandran *et al.,* 2024; Whittaker *et al.,* 2025a). Functional return-to-sport testing also showed inconsistent prediction of short-term outcomes (Gill *et*

al., 2024). MRI can answer specific diagnostic questions, such as posterior element bone stress injury (Esh *et al.,* 2020; Hoenig *et al.,* 2022), but diagnostic accuracy alone does not show that imaging-guided management improves return-to-performance outcomes.

3.7 Artificial Intelligence and Multimodal Models

AI reviews covered injury-risk assessment, running biomechanics, cycling performance, lower limb injury prediction, ACL prediction and return-to-sport modelling (Aslani *et al.,* 2026; Bullock *et al.,* 2022; Satija and Dkhar, 2026; Lou et al., 2026; Claudino *et al.,* 2019; Xiang *et al.,* 2022; Nawi *et al.,* 2025; Yuan *et al.,* 2026a; Yuan *et al.,* 2026b; Bingol *et al.,* 2026). The overall evidence shows that useful discrimination is possible, but the main weakness lies in the validation framework. Calibration was often not reported, and several reviews identified overfitting, data leakage, small samples or reliance on internal validation. In sports datasets, external validation should not be reduced to a yes or no label. Temporal validation in a later season, validation in a different athlete cohort, cross team or cross club validation, geographical validation, cross-sport validation and transportability across sensing platforms answer different deployment questions. Return to sport models make this limitation clear. Wearable or gait derived signals may improve prediction, but prospective evidence that model-guided decisions reduce reinjury or support a safer and faster return remains limited (Satija and Dkhar, 2026; Yuan *et al.,* 2026a).

3.8 Representation and Generalizability

Female-athlete representation improved in the final corpus through female-soccer recovery and FAIR injury-prevention syntheses across lower-extremity, upper-extremity and trunk/pelvic outcomes (Heming *et al.,* 2025; Goulart *et al.,* 2022; Whittaker *et al.,* 2025a; Whittaker *et al.,* 2025b). Disability and para-sport evidence was represented through wheelchair-sport and wearable-sensor reviews (Rum *et al.,* 2021; Fiorese *et al.,* 2020; Weizman *et al.,* 2024). Nevertheless, evidence remained weighted toward male, able-bodied, elite or team sport cohorts. Representation affects not only descriptive generalizability but also replication, calibration, threshold validity, transportability and clinical utility; it was therefore treated as a cross cutting translational consideration.

4. Discussion

4.1 From Measurement Abundance to Translational Scarcity

The central result is not a lack of measurable features. Across genomics, circulating biomarkers, wearables, imaging, biomechanics and AI, many variables were linked to athlete status, exposure, fatigue, injury or performance. The evidence became scarce later in the translational pathway. Only 11 reviews reached R2, one reached EC3 and 11 reached T3, while none reached T4-T5. Decision or clinical utility remained at CU0-CU1 in 74 of the 75 reviews.

These distributions apply to the prioritized review corpus and not to all eligible sports-medicine reviews. Two distinctions help explain this pattern. First, responsiveness is different from specificity. Many molecular signals change with exercise, but that does not mean they identify a unique and clinically actionable state. Second, technical performance is different from clinical utility. Strong discrimination or criterion validity does not prove that a tool adds value beyond simpler models, existing monitoring systems or routine clinical assessment.

4.2 Why Replication, Validation and Incremental Utility Remain Limiting

Independent replication should not be inferred from repeated publication. Systematic reviews may draw on the same primary cohorts, particularly in candidate genetics, concussion, wearable validation and injury prediction. The conservative R scale was used to avoid treating the number of reviews as evidence of replication. Future studies need to establish cohort independence and select validation settings that match the intended deployment. Predictive performance also needs to be judged against meaningful baselines.

An AUC or accuracy value is of limited translational value when a simpler workload measure, previous-injury history or routine clinical assessment performs similarly. Stronger evidence therefore requires calibration, comparison with relevant baseline models, assessment of incremental discrimination or reclassification, decision-curve analysis where appropriate, and prospective testing of whether model output actually changes management.

4.3 The Athlete-Centred Translational Evidence Pathway

The Athlete Centred Translational Evidence Pathway (FIGURE 2) is proposed as an organizing framework for precision sports medicine. . It asks a series of questions to check whether a candidate, marker, device, or model is useful. First, it checks whether it is related to an outcome that is important for athletes. Next, it checks whether the result can be independently repeated. It also checks whether the measurement or model has been properly validated. Further, it examines whether it provides additional information compared with simpler methods or normal care. It then considers whether this information can help in making better decisions. Finally, it checks whether these decisions can improve athlete-related outcomes without causing unacceptable burden or harm. The approach should also be practical and reproducible when implemented across different real-world teams and populations. This framework also challenges the assumption that greater information will inevitably lead to better decisions. Multimodal integration is justified only when each modality has a clear function, measurements are appropriately timed, leakage is prevented during preprocessing, predictions are calibrated, and the combined model outperforms simpler baselines. Cost, athlete burden, organizational load, privacy, and population transportability, and equity should all be taken into account during the development process rather than after the model is built. The practical goal is reliable decision support using the minimum amount of data required to fulfil the intended use.

4.4 Longitudinal Monitoring Versus Population Prediction

Two distinct statistical paradigms can be used to examine precision sports medicine. Population prediction calculates the likelihood that an athlete will perform better or be at greater risk than another. External validation, transportable thresholds, and representative cohorts are necessary for this method. A separate question is posed by individual-deviation monitoring: has this athlete's state changed meaningfully from their typical baseline?

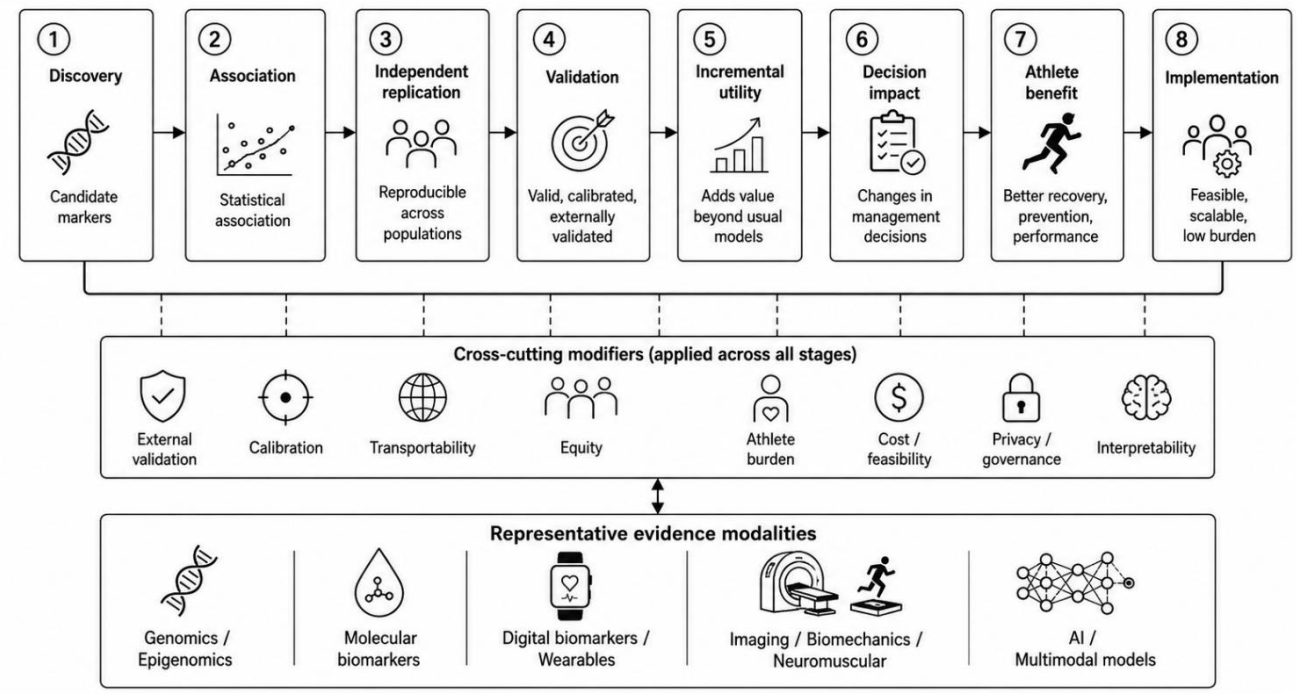

Figure 2. Athlete-Centred Translational Evidence Pathway for precision sports medicine.

This method relies more on individual reference ranges, chronological context, within-athlete variability, and repeated-measures reliability. Poorly justified universal thresholds may result from treating these two paradigms as equivalent. Therefore, longitudinal within-athlete monitoring may be a more justifiable application for many precision technologies in current practice. Repeated measurements can establish an individual baseline and make deviations easier to interpret when workload, physiology, symptoms and performance are

considered together. Even in this setting, a biomarker or model output should support reassessment and professional judgement rather than replace clinical or coaching decisions.

4.5 Research and Implementation Priorities

Figure 3 summarizes the domain-level maturity pattern within the prioritized corpus. The pattern suggests that the next research priorities should be set by the needs of translation rather than by the goal of collecting larger volumes of data. Priority actions for translational precision sports medicine are listed in table 3.

5. Strengths and Limitations

The main strength of this study is its cross-domain perspective. Genetics, biomarkers, wearables, biomechanics and AI were assessed with the same translational logic, which separates discovery, replication, validation and utility. The evidence matrix also retains features that matter for model translation, including external validation, calibration, leakage, interpretability, intended use and representation. Female-athlete and para/disability-sport evidence was deliberately retained in the final corpus. The principal limitation arises from the purposive prioritization stage. The 944 potentially eligible records did not undergo exhaustive conventional full-text adjudication by independent duplicate reviewers. The final 75-review corpus should therefore be interpreted as an auditable, predefined evidence-map corpus rather than as a statistically representative estimate of all eligible review literature. One author/reviewer finalized and graded the corpus, which means inter-rater reliability could not be assessed. Supplementary Table S2 records the disposition of all 944 records, and every numerical maturity estimate in the manuscript is restricted to the prioritized corpus. Complete item-level methodological information was unavailable for some reviews, so unsupported AMSTAR 2 judgements were not assigned. Complete primary-study citation matrices were also unavailable for all overlap clusters, which prevented numerical CCA calculation. Overlap and replication therefore remain review-level and were interpreted conservatively. The field-level data-validation audit and sensitivity analyses reduce some of these concerns, but the limitations remain relevant when comparing maturity across domains.

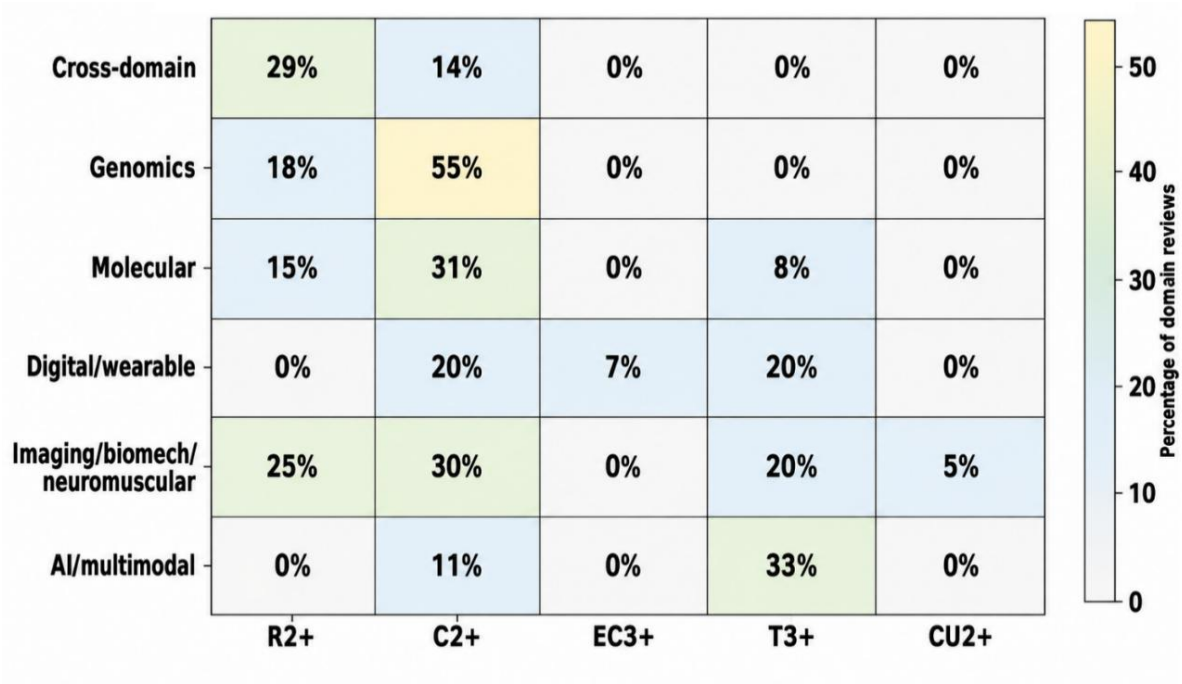

Figure 3. Translational maturity landscape across precision sports medicine domains within the prioritized 75-review corpus. Percentages are calculated directly from the S4 grading matrix.

Table 3. Priority actions for translational precision sports medicine

S. No.	Priority	Required change
1	Standardized phenotypes and intended use	Define fatigue, recovery, injury, readiness and return-to-sport outcomes before model development. State clearly whether the tool is intended for diagnosis, monitoring, prognosis or decision support.
2	External validation	Validate across time, teams, clubs, competition levels, countries, sexes and, where relevant, sensing platforms before proposing new architectures.
3	Calibration and incremental utility	Report calibration and improvement over simple baselines or usual care, rather than discrimination alone.
4	Prospective marker / model-guided trials	Test whether biomarker-, wearable- or model-guided decisions change management and improve athlete-relevant outcomes.
5	Representative populations	Include female athletes, para-athletes, youth athletes and geographically diverse groups in validation by design rather than only as post hoc subgroups.
6	Transparent multimodal pipelines	Report data alignment, missingness, feature selection, leakage control, preregistration and code or model availability.
7	Burden-aware implementation	Evaluate cost, athlete burden, privacy, acceptability and organizational feasibility together with predictive performance.

6. Conclusion

This review-level translational evidence map shows that precision sports medicine is moving beyond isolated biomarkers toward combined digital, biological and biomechanical profiles. However, translational maturity in the prioritized corpus remains uneven. Most review-level evidence supports discovery, association, replication or validation for a specific intended use, rather than demonstrated decision impact. Wearable, imaging and neuromuscular applications provide some of the clearest validation signals. Molecular biomarkers and candidate-gene evidence remain limited by specificity and heterogeneity. AI offers a route to combine complex data, but broad implementation still requires stronger evidence for external transportability, calibration, leakage control, incremental value and prospective decision impact. Progress in this field will depend less on adding more candidate signals and more on validating a smaller set of useful signals against real athlete-management decisions and outcomes.

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