The AITIM (AI-integrated talent identification to management) Bridge: An AITIM framework for sustainable athlete Development in elite sport systems

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Artificial Intelligence in Sport; Athlete Development Pathways; Ethical and Responsible AI; Organisational Governance; Strategic Talent Management; Talent Identification Systems; Talent Retention

Abstract

Purpose: This study introduces the concept of the AITIM Bridge, an innovative model that explains the ways in which the outputs generated by an artificial intelligence system might be incorporated into strategic talent management systems to ensure the sustainable development of athletes in sport. This study addresses the gap between AI-enabled talent identification and the organisational processes governing athlete development, wellbeing, and retention through a structured interdisciplinary synthesis of sport management, artificial intelligence, and organisational literature (Moher et al., 2009; Tranfield et al., 2003; Torraco, 2005). The current investigation was designed to address the gap between the potential offered by the use of AI in talent identification and the organisational processes through which athlete development, wellbeing, and retention are managed.

Design/methodology: The qualitative-dominant systematic literature review was conducted using the PRISMA method, thematic comparison, cross-study pattern analysis, and conceptual integration, searching the Scopus, Web of Science, SPORTDiscus, and Google Scholar databases, and using the inclusion criteria to identify relevant literature published between 2005 and 2025.

Findings: The literature is fragmented across three relatively disconnected areas of sport management, artificial intelligence, and organisational studies, with the areas of talent management and athlete wellbeing and retention being relatively less well-represented in the literature. The literature on the use of AI in talent identification focuses on the efficiency and data capture potential offered by the technology, while the literature on talent management focuses on the need for interdisciplinary support and organisational fit, although little attention is given to the mediation process by which the outputs generated by the technology might be filtered before being fed into the athlete development process.

Practical implications and conclusions: The AITIM Bridge is an innovative model that explains the ways in which the outputs generated by an artificial intelligence system might be incorporated into strategic talent management systems to ensure the sustainable development of athletes in sport. The model recasts the use of AI as an organisational competency, rather than an autonomous recruitment tool, and provides sport organisations with the opportunity to develop a system through which the use of technology might be governed.

Introduction

Artificial intelligence has evolved from being peripheral and experimental to becoming a recognizable part of elite sport systems. The appeal of AI in elite sport lies in its ability to process large amounts of data, process information rapidly, and offer objective insights. The use of AI has led many coaches and analysts to believe that the future of talent identification will be centered around enhancing performance through AI.

This, however, is just one part of a much longer athlete development continuum. Once an athlete has been identified as having talent, there remains an extended process involving entry into development systems, support, progression, wellbeing, transition, and retention. As research in sport science has shown, there remains no guarantee that elite performance will be forthcoming, nor will there be any guarantee that elite performance will be maintained (Williams & Reilly, 2000; Vaeyens et al., 2008). As Martindale et al. (2005) noted, athletes develop within an environment that is influenced by factors such as coaching quality, psychosocial support, and organisational culture (Henriksen et al., 2010; Stambulova et al., 2009). The managerial implications, therefore, mean that talent systems should be designed, rather than merely resourced.

The strategic approach to talent management is an important theoretical tool to address this problem. In the context of management studies, talent management is described as the coordinated process of identification, development, and retention of individuals with high potential, consistent with organisational strategy (Collings and Mellahi, 2009; Lewis and Heckman, 2006). The application of this concept to the sport domain means that the focus would move beyond the efficiency of recruitment to a system that incorporates performance, educational, and welfare factors, as well as psychology and succession planning. Following this logic, Anastasieski and Menon (2025) offered the Integrated Talent Sustainability Framework and the Talent Management Unit (TMU) as a cross-functional entity that is capable of linking identification and retention. Their findings demonstrate that retention is not a simple consequence of successful coaching but is actually a product of integrated management, psychosocial support, and institutional congruence.

The emergence of AI technology introduces a new theoretical problem. The AI technology literature is currently focused on the accuracy of prediction, movement recognition, and performance, while the organisational and human resource literature is concerned with governance, decision-making, and continuity. The connection between these two bodies of literature is missing, and without such a connection, AI technology is assumed to exist as a self-contained entity, potentially producing a technocratic approach to decision-making that treats athletes as a product of computer programming rather than a developing entity that is part of a social system.

This paper seeks to bridge this gap through the development of the AITIM Bridge, where AITIM stands for 'AI Integrated Talent Identification to Management.' The model conceptualizes the role of AI as an upstream 'intelligence' function, where the output requires human interpretation before being considered as an input to development decisions. The paper conducts a qualitative-dominant systematic review, synthesizing the literature on the application of AI in sport, talent identification, talent management, wellbeing, and retention, and then integrates these bodies of literature into a new model. The innovation is the reconnection of the application of AI in talent identification to the wider talent management system, the inclusion of wellbeing and ethics in the application of AI, and the extension of the previous TMU model-based research path into a model of sustainable athlete development governance.

Notwithstanding the pace of technological progress, the theoretical development of artificial intelligence integration into elite sport systems remains embryonic. Current scholarship is marked by a profound dichotomy between technocentric models that place predictive optimisation at the core and organisational perspectives that place developmental coherence at the core of decision-making. Each of these perspectives appears to operate in a vacuum, and the current understanding of the translation of AI-based understanding into talent decision-making is piecemeal and indicative of a theoretical disconnect between the identification of talent and the management of talent. This study seeks to redress the disconnect between the two perspectives with a conceptual model of translation between the domains.

Literature Review

Talent Identification and The Limits of Predictive Certainty

Research in the area of talent identification has traditionally attempted to improve the accuracy of identifying elite performance in the future. In the early days of sports science research, physiological, technical, and anthropometric factors, in addition to coach observation, were the focus (Williams & Reilly, 2000). More recent research has challenged the narrow focus of the initial research, suggesting that the concept of talent must be viewed as a multifaceted rather than a unidimensional concept, which can be identified at one specific point in the development process (Martindale et al., 2005; Vaeyens et al., 2008). This is an important consideration, as many development programs overemphasize performance and physical maturation in the short term.

One of the most concerning issues in the research has been the issue of selection bias, as early maturation groups tend to dominate in the short term, which can lead scouts to overemphasize the value of early maturation (Bailey & Collins, 2013). In fact, Cobley et al. (2009) show the relative effects of age and maturation on the selection process in youth sports, which has clear implications for the use of artificial intelligence in the selection process, as the algorithm would likely perpetuate these biases, which are so clearly problematic in the research.

In the area of football, the organisational structures in which the research is conducted are clearly linked to the definition of the concept of talent identification. Relvas et al. (2010) show the differences in the relationship between the youth domain and the first team domain in elite clubs, which has clear implications for the quality of transition in the development process. In a review of male youth football, Rongen et al. (2018) suggest that predictive accuracy is limited in the selection process, as the process is clearly linked to the interplay of technical, psychological, social, and environmental factors, which must be taken into consideration in the identification process.

Artificial Intelligence in Sport: Capability and Governance Gaps

Three forms of development in the use of AI in sports can be distinguished: performance analysis, injury prevention, and scouting. Machine learning can be used to make classifications, recognize technical flaws, and generate probabilistic inferences from large data sets. In principle, these developments extend the evidence base available to coaches and analysts. Three recurring issues can, however, be distinguished in the literature.

The first is the issue of explainability: many machine learning technologies are opaque, meaning that the results are hard to interpret, particularly for non-technical decision-makers, which may lead to operationalization without a clear understanding of what the model is identifying or assuming (Davenport & Ronanki, 2018). The second issue is fairness: the literature on responsible AI research has shown that machine learning can perpetuate inequality structures in terms of age, geography, race, gender, position, or socioeconomic status (Mittelstadt et al., 2016; Binns, 2018). According to Floridi et al. (2018), the implementation of AI in sports must be accompanied by an explicit set of governance principles, including transparency, accountability, and human oversight. The third issue is the under-theorization of the organisational domain: the literature on the implementation of machine learning in sports primarily discusses the extent to which the model improves prediction or recognition performance, but rarely addresses the extent to which the results are processed in the decision process, how conflicts are resolved, or how the effects are fed back into the model.

Talent Management and Organisational Integration

The talent management literature offers a different starting point. Strategic talent management concerns the coordinated identification, development and retention of high-potential individuals in ways that align with organisational strategy (Collings and Mellahi, 2009). Although the concept is debated (Lewis and Heckman, 2006), consensus exists that it is not reducible to administrative HR practice. It requires system thinking, long-term planning and clear organisational ownership.

Dries (2013) adds a psychological dimension by arguing that talent should be comprehended as dynamic, socially situated and developmental. In sport, this aligns with athlete-centred models that emphasise progression planning, psychosocial support and coordinated communication among stakeholders (Cote and Gilbert, 2009; Henriksen et al., 2010). Sport-specific studies reinforce the importance of organisational integration. Taylor and McGraw (2006) expose that HRM in sport often remains administratively oriented and poorly aligned with high-performance needs. Relvas et al., (2010) further demonstrate that the organisation of elite football clubs shape transition quality and pathway coherence.

These findings underpin the significance of the TMU concept. In the author's earlier work, the TMU was proposed as a specialised, cross-functional unit responsible for coordinating development pathways, wellbeing monitoring, performance data integration and retention planning (Anastasieski and Menon, 2025). The theoretical value of the TMU lies in its capacity to bridge departments that often operate in isolation. The present review extends that concept by examining what must happen before algorithmic information can be responsibly absorbed into such a unit.

Retention, Wellbeing and Sustainability

Retention is shaped by belonging, psychological safety, clarity of progression, injury management, cultural integration and realistic transition planning (Stambulova et al., 2009; Henriksen et al., 2010). High-potential athletes may leave not because they lack ability, but because they encounter fragmented communication, uncertain pathways or weak support systems. This makes retention a strategic outcome of organisational design rather than a passive consequence of selection.

Anastasieski and Menon (2025) argued that retention should be understood as a product of integrated talent management linking development planning, institutional integration, performance and wellbeing monitoring, and retention strategy under TMU coordination.

That logic is directly relevant to AI-enabled systems because algorithmic identification gains value only when connected to structures that sustain development over time. Across the literature, then, a clear gap emerges. AI studies are strong on signal generation. Talent management studies are strong on support and coordination. Wellbeing studies are strong on human development and transitions. What is missing is a formal architecture connecting these domains. The AITIM Bridge is developed in response to that gap.

Research Methodology

This approach is particularly appropriate given the fragmented and interdisciplinary nature of the literature, where theory-building requires integration across domains rather than aggregation within a single methodological tradition (Tranfield et al, 2003; Torraco, 2005). In view of the fact that the included studies differ in epistemological commitment, units of analysis, and measures of outcome, the objective of the review is not statistical synthesis, but explanatory synthesis (Moher et al., 2009). The review therefore prioritises conceptual coherence, governance relevance, and developmental interpretation, enabling a framework to be generated from patterns that cut across sport analytics, thereby strengthening the methodological positioning of the study as theory-building rather than purely descriptive synthesis.

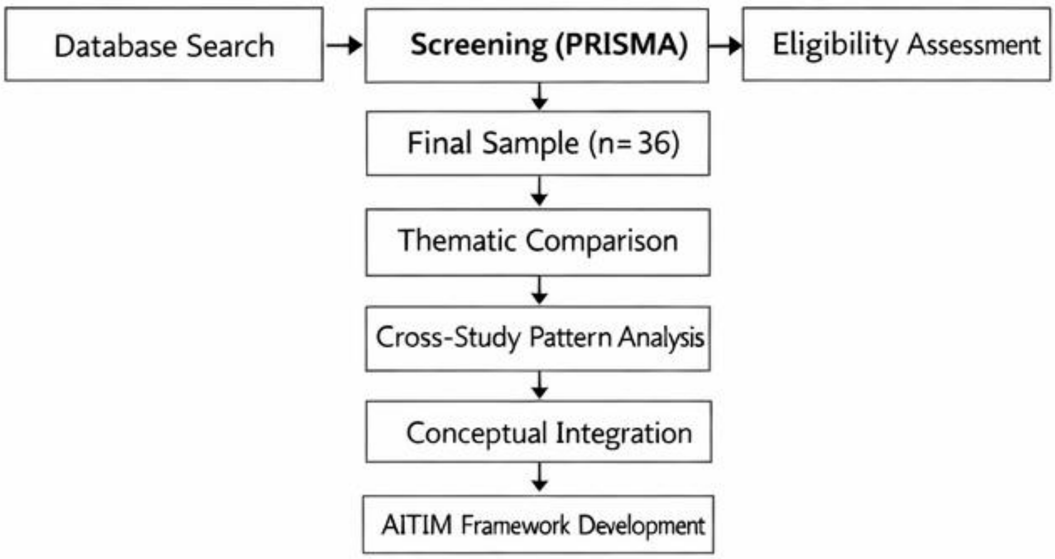

Figure 1: Methodological Process of Systematic Review and Conceptual Framework of Development

Search Strategy and Sources

A PRISMA-informed review procedure guided the search, screening and selection stages (Moher et al., 2009). Searches were conducted across Scopus, Web of Science, SPORTDiscus, and Google Scholar, because these databases collectively capture the main literature in sport management, sport science, management research and interdisciplinary technology studies. Search strings combined keywords around four themes: artificial intelligence, talent identification, talent management and athlete development or retention. Examples included “artificial intelligence” AND sport AND scouting; “talent identification” AND football OR elite sport; “talent management” AND sport; and “algorithmic bias” and “performance decision making”. The search window was set from 2005 to 2025. Reference list snowballing was used to locate additional relevant sources from key review papers and seminal articles. The search was limited to English-language peer-reviewed journal articles, authoritative book chapters and highly relevant conceptual works that directly informed framework development.

Inclusion and Exclusion Criteria

Studies were included when they examined AI, machine learning, data analytics or computational assessment in sport; analysed talent identification or athlete selection systems in elite or pathway sport; addressed strategic talent management, organisational development systems or retention-related structures; or focused on athlete wellbeing, transition and sustainability within development pathways. Studies also had to contribute conceptually or empirically to the relationship between identification, development, organisational decision making and long-term outcomes.

Studies were excluded if they were purely technical optimisation papers with no organisational or developmental relevance, if they focused exclusively on match prediction unrelated to talent systems, or if they lacked sufficient methodological transparency. Conference abstracts and unrefereed opinion pieces were also excluded.

Selection Process and Sample

The search generated 312 records. After duplicate removal, 276 records remained. Title and abstract screening removed 198 records that did not fit the review objectives. Seventy-eight full texts were then assessed in detail. Of these, 42 were excluded because they lacked organisational relevance, focused only on technical model performance, or did not substantially engage with talent identification, management or athlete pathway issues. Thirty-six studies were retained for final synthesis. The figures are presented in Table 1 and Figure 2.

The final sample covered several overlapping domains: talent identification and youth development in sport; strategic talent management and organisational integration; AI, analytics and algorithmic governance and psychosocial development, career transitions and supportive environments. The interdisciplinary character of the sample was necessary because the research question itself sits between domains rather than fully within one of them. To strengthen methodological consistency, screening decisions were guided by predefined inclusion criteria and iteratively cross-checked during the review process to ensure alignment between conceptual relevance and selection outcomes. Ambiguous cases were re-evaluated in relation to research objective, thereby enhancing internal consistency and reducing selection bias.

Stage	Description	Number
Identification	Records identified through Database Searching	312
Identification	Records after Duplicate Removal	276
Screening	Title and Abstract Records Screened	276
Screening	Title and Abstract Records Excluded	198
Eligibility	Full-Text Articles Assessed	78
Eligibility	Full-text Articles Excluded	42
Included	Studies included in Qualitative Synthesis	36

Table 1. PRISMA summary of study selection process

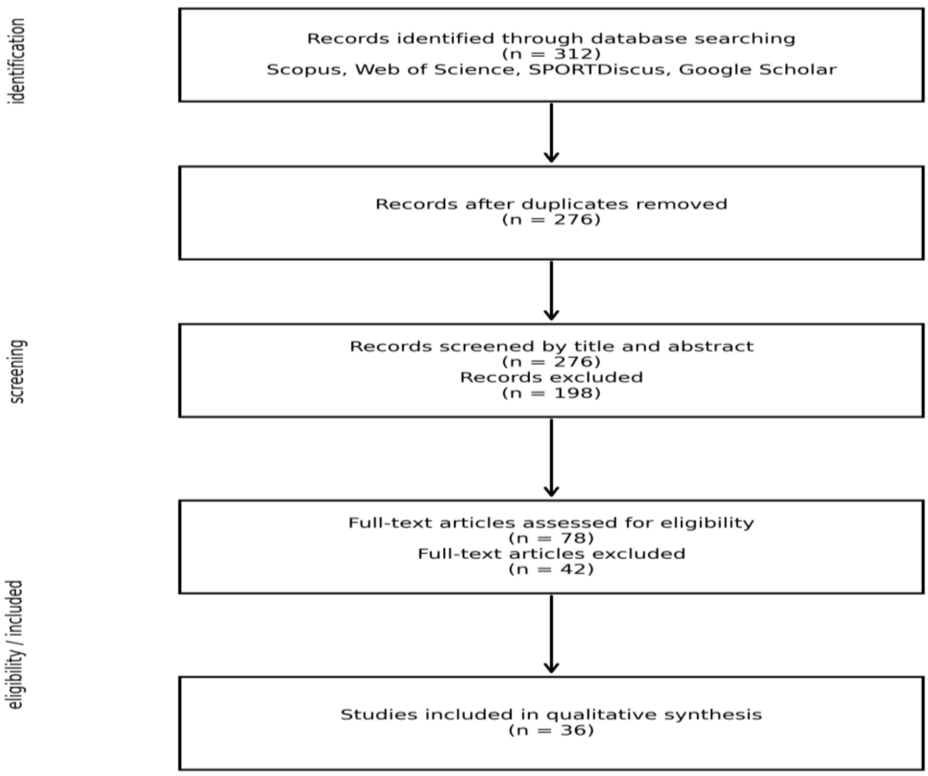

Figure 2: PRISMA flow diagram of the study selection process

Analytic Process

The analysis proceeded through three linked stages. The first stage, thematic comparison, identified recurring concepts across the literature. Themes included predictive efficiency, multidimensional assessment, organisational integration, psychosocial support, governance, fairness, progression planning and retention. This stage mapped how each literature cluster framed the problem.

The second stage, cross-study pattern analysis, moved from thematic description to relational interpretation. It examined whether recurring configurations could be identified across studies. For example, studies of integrated development systems repeatedly linked coordination, clear progression pathways and psychosocial support with stronger retention and smoother transitions (Relvas, et al., 2010; Henriksen et al., 2010; Anastasieski and Menon, 2025). By contrast, AI-oriented studies frequently emphasised algorithmic assessment while leaving governance and contextual interpretation under-specified.

The third stage, the conceptual integration stage, synthesised the findings from the first two stages into an explanatory model. The purpose was to identify the missing structural mechanisms linking AI-generated talent signals to sustainable organisational outcomes. The framework emerged through abductive movement between the literature and the author's prior TMU-based theory, allowing the final model to function as an extension rather than a disconnected invention (Anastasieski and Menon, 2025).

Analytical trustworthiness was enhanced through iterative comparison across studies and constant movement between data extraction and conceptual interpretation. Themes were not treated as isolated categories but were examined relationally, allowing patterns to emerge across disciplinary boundaries. This iterative and abductive process strengthened the explanatory depth of the synthesis and reduced the risk of superficial thematic aggregation.

Methodological Boundaries

Considering the diversity of the literature, the review stresses concept development over quantitative comparison. This study seeks to explain and support the development of frameworks. The analysis makes no claim about causation that any organisational design will produce better employee retention outcomes than any other.

Instead, it identifies recurring patterns strong enough to justify a coherent conceptual architecture. This stance is appropriate because the paper asks not whether AI models can classify talent, but how those classifications should be governed, interpreted and embedded within development systems.

This study adopts an integrative systematic review approach, combining structured literature identification with theory-building synthesis. Unlike aggregative reviews that seek statistical generalisation, the present approach prioritises conceptual development and interdisciplinary integration, which is particularly appropriate for examining complex phenomena spanning artificial intelligence, organisational systems, and athlete development.

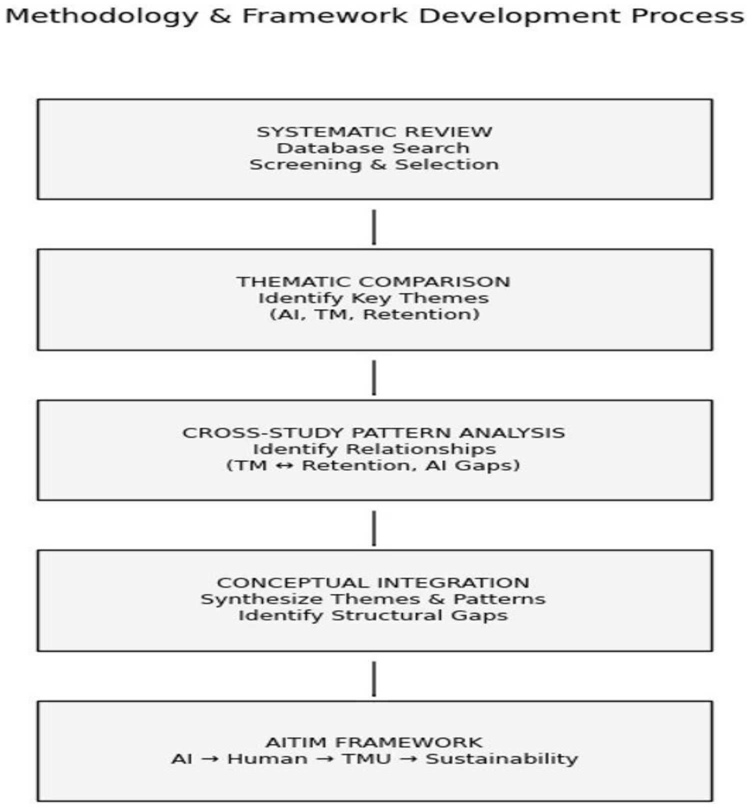

Figure 3. Multi-stage analytical process used for thematic comparison, cross-study pattern analysis and conceptual integration

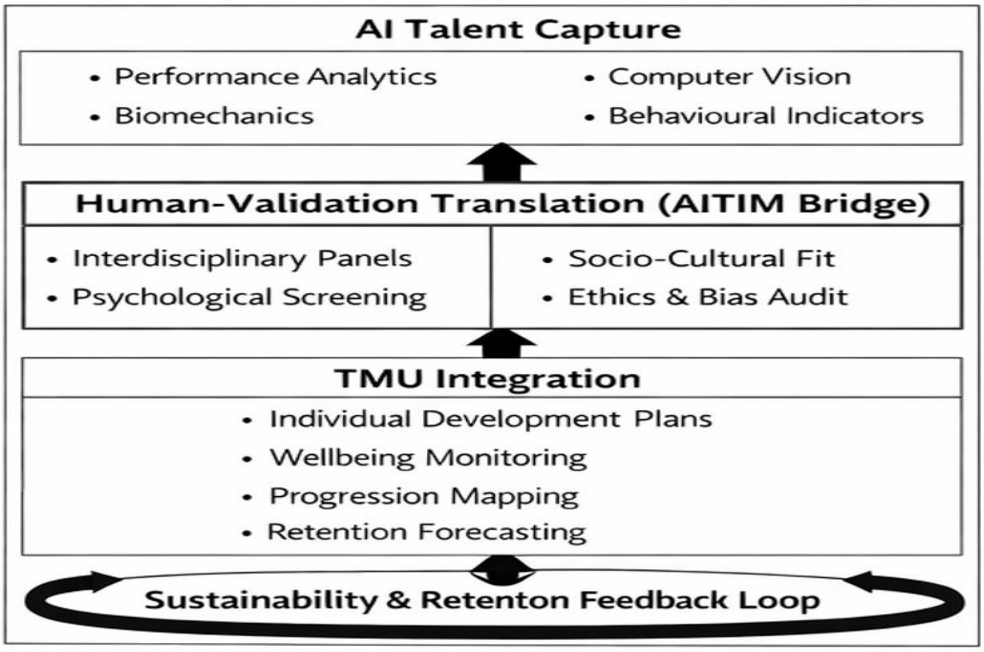

Figure 4: The AITIM Bridge Framework for AI-Integrated Talent Identification and Management in elite sport systems.

Findings and Results

The synthesis generated four major findings. The first concerns the fragmentation of the literature itself. The second concerns the asymmetry between AI capability and governance. The third concerns the association between integrated talent systems and sustainable pathway outcomes. The fourth is the theoretical necessity of a translation layer between algorithmic output and talent management action. These findings directly inform the development of the AITIM Bridge Framework, which addresses the identified structural disconnect between AI capability and organisational talent systems by introducing a governance-based translation mechanism linking identification to development, wellbeing, and retention outcomes.

Descriptive Overview of The Literature

The included studies were distributed across sport science, sport management, human resource management, organisational studies and AI ethics. Methodologically, the sample encompassed systematic reviews, conceptual papers, comparative case studies, qualitative interview studies and applied analytics research. Football dominated the sport-specific literature, although relevant insights also emerged from track and field, broader elite youth sport and general management scholarship. This reinforces the argument that the problem is inherently interdisciplinary.

A descriptive pattern was immediately visible. Studies focusing on AI or analytics prioritised detection, classification or prediction. Their language centred on accuracy, efficiency, data richness and technical performance. In contrast, talent management and athlete development studies centred on progression, fit, support, organisational coherence and long-term outcomes. Only a small minority of studies bridged these domains directly. The gap is itself a result, because it indicates that AI and talent management are evolving in parallel rather than as a unified field.

Thematic Comparison

The thematic comparison stage identified three broad clusters and one integrative deficit. The first cluster concerned AI-enabled talent capture. Across this literature, AI was positioned as a mechanism for extending observational reach, processing complex variables and identifying hidden indicators of performance potential. Yet themes of explainability and ethical oversight were far less developed than those of detection and optimisation.

The second cluster concerned organisational talent management. Dominant themes were coordination, cross-functional support, developmental planning, psychosocial monitoring and retention strategy. Strategic talent management research emphasised the importance of aligning high-potential development with organisational objectives (Collings and Mellahi, 2009; Dries, 2013). Sport-specific studies translated that principle into integrated pathway systems, structured mentorship, first-team alignment and supportive cultures. The author's prior TMU-based work fits strongly in this cluster because it formalises the organisational infrastructure needed to move from talent discovery to talent sustainability (Anastasieski and Menon, 2025).

The third cluster concerned athlete wellbeing, development environment and transition. Themes here included psychological safety, identity, belonging, educational support, role clarity and transition management. These studies consistently challenged purely performance-centric understandings of development. They argued that sustainable pathways depend on holistic support and that attrition often reflects environmental mismatch rather than individual deficiency (Henriksen et al., 2010; Stambulova et al., 2009).

The integrative deficit became visible when these clusters were compared. AI studies rarely specified how athletes should be interpreted beyond performance data. Talent management studies rarely theorised how algorithmic inputs should be governed. Wellbeing and transition studies rarely addressed AI at all. The literature therefore offered strong components but no comprehensive bridge.

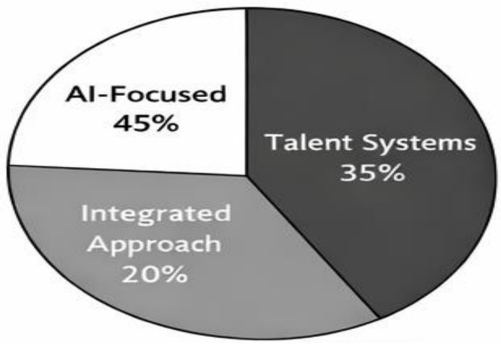

Figure 5: Distribution of Reviewed Studies across Thematic Domains

Cross-Study Pattern Analysis

The cross-study pattern analysis revealed several recurring relationships. First, studies of integrated organisational systems repeatedly associated cross-functional coordination with stronger developmental continuity. Relvas et al. (2010) found that clubs with better alignment between youth and professional domains produced smoother progression structures. Henriksen et al. (2010) revealed that successful development environments were characterised by coherence, support and institutional integration. Anastasieski and Menon (2025) extended this by arguing that TMUs can operationalise such coherence through dedicated management of development, wellbeing and retention.

Second, where organisational structures were weak or fragmented, retention and pathway clarity suffered. Taylor and McGraw (2006) highlighted the limitations of administratively oriented HRM in sport organisations. Broader talent management literature similarly warns that talented individuals disengage where ownership of development is diffuse or strategically misaligned (Lewis and Heckman, 2006; Dries, 2013). Sustainable talent outcomes are therefore strongly connected to organisational, not merely to scouting quality.

Third, AI-related studies tended to foreground capability while under-specifying governance. This pattern does not imply that AI research ignores ethics entirely, but rather that ethical and organisational concerns usually appear as secondary reflections rather than integral features of implementation. However, sport analytics studies often demonstrate what can be measured or predicted, yet leave unresolved who should interpret those outputs, under what conditions, and with what developmental responsibilities.

Fourth, the pattern analysis showed that retention, wellbeing, and person-organisation fit are not natural downstream outcomes of better identification. They require active structures of translation, support and monitoring. This finding is central to the logic of the AITIM Bridge. If sustainable outcomes depend on integrated management rather than on predictive accuracy alone, then AI cannot move directly from data capture to decision authority. A governance intermediary is required.

The AITIM Bridge Framework

The conceptual integration stage led to a four-layer framework. The first layer is AI talent capture. This layer encompasses video-based computer vision, performance analytics, biomechanical profiling and pattern recognition systems. It treats algorithmic output as a preliminary intelligence stream that may highlight patterns and probabilities, but which remains contingent on data quality, model design and contextual fit. Transparency, explainability and bias awareness are therefore core design principles at this stage.

The second layer is human-validation translation, which constitutes the core innovation of the framework. In this layer, AI-derived signals are interpreted by cross-disciplinary actors, including coaches, analysts, psychologists, player care specialists and talent managers. The purpose is to convert algorithmic outputs into contextually meaningful developmental insight. This layer addresses questions the algorithm alone cannot resolve. Does the athlete's psychosocial profile support the pathway implied by the model? Is the player's learning style or resilience compatible with the organisational environment? Are there cultural, educational or family factors that affect readiness? Are the data likely to reflect historical bias or current overperformance? The translation layer therefore functions as both an interpretive and an ethical checkpoint.

The third layer is TMU-embedded integration. Once AI signals have been validated contextually, they are embedded within a Talent Management Unit or equivalent cross-functional structure. Here they inform individual development plans, progression mapping, wellbeing monitoring and retention-risk assessment. This layer extends the earlier ITSF/ TMU model by making AI-derived insight an organisational input rather than a standalone verdict (Anastasieski and Menon, 2025).

The fourth layer is the sustainability feedback loop. Athlete wellbeing, retention, transition success, developmental continuity and person-organisation fit become not just outcomes to be observed, but signals that could reshape future identification criteria. This creates an adaptive system in which both management practice and model assumptions can be refined. Overall, the findings indicate that the literature supports a mediated rather than direct relationship between AI and talent decision making. AI contributes powerful upstream capabilities, but sustainable outcomes are consistently associated with interdisciplinary support, organisational coherence and developmental governance. The central result of the review is therefore not simply that AI needs ethics, but that AI in talent systems requires a structured bridge into talent management.

Continuity with the Prior ITSF/TMU Framework

The AITIM Bridge should be understood as an extension of the author's earlier TMU-based work rather than as a disconnected model. In the prior ITSF framework, the central problem was the disjunction between identifying talent and retaining it sustainably (Anastasieski and Menon, 2025). The present review illustrates that AI introduces a new but related disjunction: the gap between identifying talent computationally and managing that talent developmentally. The TMU remains central, but its role expands. It becomes the organisational site where validated AI insight is converted into developmental practice.

This continuity strengthens the theoretical credibility of the AITIM model because it grows from an existing management logic rather than replacing it. The ITSF argued that development planning, institutional integration, wellbeing monitoring and retention strategy require coordination under a dedicated unit. The AITIM Bridge retains this structure by ensuring that AI-derived insights are integrated without bypassing management systems. In effect, the model claims that AI does not remove the need for a TMU; rather, it intensifies that need. The more data-rich and technically powerful identification systems become, the greater the need for a structured unit capable of interpreting, contextualising and governing their use.

A key implication of these findings is that the current trajectory of AI adoption in sport risks reinforcing a technocentric model of decision-making in which computational outputs are implicitly privileged over contextual expertise (Davenport and Ronanki, 2018; Woods et al., 2020). Such a trajectory may not only fail to improve talent systems but may actively distort them by embedding historically biased patterns within apparently objective models (Mittelstadt et al., 2016; Noble, 2018). AI systems are trained on data shaped by relative age effects, early selection bias, or unequal access to development opportunities, then those distortions are not neutralised through automation but instead risk being amplified (Cobley et al., 2009; Baker et al., 2012). This raises a fundamental concern: without governance structures, AI does not remove bias, but can legitimise and scale it (Floridi et al., 2018; Wachter et al., 2021). The AITIM Bridge therefore positions governance not as a supplementary layer, but as a necessary condition for the responsible integration of AI within athlete development pathways.

Discussions

The AITIM Bridge advances several ongoing debates in sport management and applied AI. Most importantly, it shifts the unit of analysis from the algorithm to the system in which the algorithm operates. Much of the discourse around AI in sport remains technologically centred, framed in terms of predictive superiority, data quality or model performance. These are important issues, but they are incomplete if detached from the organisational settings in which athlete futures are shaped. The present review suggests that the real managerial challenge is not simply whether AI can identify potential, but whether organisations can govern AI in ways that preserve contextual judgement, developmental fairness and long-term sustainability.

Theoretical Contributions

The contributions of this paper are threefold in addressing the literature on the topic of artificial intelligence and talent management in elite sport. First, this paper proposes a new perspective on the interaction between artificial intelligence and talent identification and development in elite sport. Contrary to existing literature that considers artificial intelligence as a support to current scouting methods, it highlights a basic mismatch between the outcome of algorithms and the process of decision making within the organisation. The AITIM Bridge Framework solves this mismatch problem by proposing a translation framework that has theoretical foundations.

The findings of this study suggest that the prevailing trajectory of AI adoption in sport is conceptually incomplete. Rather than representing a linear improvement in talent identification, AI introduces a structural challenge, the separation of analytical capability from organisational meaning. The existing model assumes that increased predictive power automatically translates into better decision making. Such an assumption is theoretically problematic because it fails to recognize the interpretative, contextual, and developmental aspects that constitute talent development in organisations. The AITIM Bridge makes its contribution to the debate by redefining the role of artificial intelligence not as a replacement of decision-making, but as an input requiring translation.

Second, the study introduces the Human-Validation Translation layer as a novel theoretical construct. This represents the core innovation of the AITIM Bridge Framework and formalises the previously untheorised process through which AI-generated talent signals are evaluated in relation to psychological, socio-cultural, and organisational factors. In effect, the framework moves beyond purely descriptive investigations concerning biases and fairness in AI to incorporate these aspects in a systematic approach to decision making (Mittelstadt et al., 2016; Floridi et al., 2018).

Third, the study extends talent management theory into AI-enabled environments by positioning Talent Management Units (TMUs) as the organisational locus through which validated AI insights are operationalised. This integration aligns talent identification with long-term athlete development, wellbeing, and retention, thereby shifting the analytical focus from predictive performance to sustainable pathway outcomes (Henriksen et al., 2010; Relvas et al., 2010). Collectively, these contributions reposition AI as a managed organisational capability within high-performance sport systems rather than a standalone technological solution.

Why the Human-Validation Translation Layer Matters

The most distinctive element of the framework is the human-validation translation layer. This layer is not an advisory checkpoint added after the algorithm has produced outputs. This layer constitutes the conceptual basis of the model, distinguishing the AITIM Bridge from direct-input systems in which the AI outputs control the decision process directly, without any intermediary. According to the review, there are three main shortcomings of direct-input systems.

First, they misunderstand the nature of talent. Talent is developmental, relational and context-sensitive. A player who appears highly promising in one data environment may not be ready for a specific club culture, tactical model or developmental pace. Likewise, an athlete with a lower immediate score may possess resilience or learning qualities that make long-term progression more likely. Human-validation translation keeps those dimensions in view.

Second, direct-input systems risk legitimising bias under the cover of computation. If historical data reflect unequal opportunity, maturity effects or hidden exclusion, then a model trained on those data may reproduce injustice with technical credibility. Human-validation translation introduces a mechanism for interrogating rather than merely consuming model outputs.

Third, direct-input systems can create organisational dependency on specialists who control the technical architecture but not the developmental consequences. In contrast, the translation layer distributes responsibility across interdisciplinary actors, which is more consistent with how sustainable athlete development actually operates.

Managerial Implications and Conclusion

From a practical standpoint, the AITIM Bridge suggests that sport organisations should avoid treating AI procurement as equivalent to talent systems transformation. Buying technology or hiring analysts does not create a sustainable pathway. Organisations should instead inquire who is accountable for translating algorithmic information into development decisions, how psychosocial and wellbeing considerations are incorporated alongside performance data, and how retention and transition outcomes are used to evaluate whether the system is working.

For clubs and academies, the framework points towards the value of an explicit TMU or equivalent cross-functional unit. Such a unit should include technical, developmental and welfare expertise and could own the pathway from AI signal to support plan. This reduces the likelihood that AI remains siloed within analytics departments. For governing bodies, the framework suggests that standards for AI implementation in talent systems should extend beyond privacy and data protection toward fairness, explainability, auditability and developmental accountability.

In conclusion, this paper addressed a structural gap in the literature: the absence of a framework connecting AI-enabled talent identification to sustainable organisational talent management. The AITIM Bridge integrates these domains through four linked layers and argues that AI should inform talent systems without bypassing the organisational and human processes through which athlete development is responsibly managed. Sustainable athlete pathways are not generated by data alone. They are produced when technology is governed within structures that preserve context, fairness support and long-term developmental logic.

Implications for Capability, Policy and Implementation

The model framework emphasizes that an essential element in the effective implementation of AI technology involves organisational capabilities alongside software. The model states that it is crucial for coaches, psychologists, and talent management experts to have enough knowledge to critically assess the results generated by the AI system, whereas analysts should possess sufficient organisational understanding to recognise both the capabilities and limitations of the models. Therefore, the effective implementation of AI technology in sports depends not only on computational skills but also on interdisciplinary capabilities. In other respects, the organisation risks being misled.

A further implication is related to governance architecture. Numerous clubs have their analytics, welfare, and coaching divisions, but such divisions can work within different time frames and success criteria. Whereas analytics will focus on predictability, coaching will focus on achieving results, while welfare personnel will pay attention to immediate wellbeing. In order to reconnect all these activities in one flow again, it is suggested to utilize the concept of the AITIM Bridge. The value of the TMU in this regard is seen from the perspective that it allows establishing an identifiable organisational point within the flow.

It is relevant from a regulatory perspective. Regulators and professional leagues are increasingly examining the issue of ethics in data gathering, surveillance, and use of algorithms in decision making in sport, but their focus tends to be on privacy, consent, and compliance. While these are important issues, they do not consider developmental justice considerations. Even if a process is compliant with all the regulatory requirements related to data and its use, it may still produce results that are inequitable from a developmental perspective, because of the emphasis on easily quantifiable talent and disregard for those who have been historically excluded.

A further implication pertains to organisational culture. Incorporating sophisticated forms of AI in dysfunctional or misaligned cultures may simply worsen existing issues instead of solving them. As such, in performance-oriented environments focused on short-term results, AI will make short-term thinking even more efficient. Similarly, in environments with fragmented pathways and processes, AI is anticipated to exacerbate silo thinking by adding even more specialised domains. Building on the foregoing considerations, it is evident that a critical evaluation of organisational culture, communication processes, and developmental philosophy should precede, or at minimum accompany the adoption of technological innovations. The position aligns with findings indicating that, within effective talent development environments, the value of data lies not in its volume but in its coherence and alignment with a shared objective (Henriksen et al., 2010).

From a methodological perspective, the proposed model represents a further advancement in sport management scholarship. While systematic reviews frequently emphasise the value of interdisciplinary approaches, the present study demonstrates that such integration could be operationalised systematically through thematic comparison across studies, identification of recurring patterns, and their subsequent synthesis. This structured interdisciplinarity enables fragmented bodies of literature to be consolidated into theory-building processes. In this regard, the AITIM Bridge serves as a concrete exemplar of such integrative efforts.

Limitations and Direction for Future Research

There are several weaknesses associated with this study. First, the research is purely conceptual and based on the systematic synthesis of existing literature. While this methodology can effectively contribute to theoretical development in areas that are fragmented and interdisciplinary (Tranfield et al., 2003; Torraco, 2005), the AITIM Bridge Framework has not been subjected to empirical testing in practical organisational settings. Second, the literature analysed shows significant heterogeneity in terms of methodology, discipline, and analysis, making it difficult to compare different papers. Third, while the framework should be applicable to all elite sports, empirical organisational evidence is available primarily for football environments, and modifications might be required to use it in other disciplines.

Future research should focus on empirical validation of the AITIM Bridge Framework through multi-case studies, longitudinal tracking of athlete pathways and comparative analysis between AI-integrated and traditionally managed systems. Further work is also required to develop governance protocols for AI implementation in sport, including ethical auditing mechanisms, explainability standards, and decision accountability structures (Wachter et al., 2021). Such research could provide critical insight into how AI can be operationalised within sustainable and ethically responsible talent systems. Ultimately, the effectiveness of artificial intelligence (AI) in elite sport will depend not on its capacity to replace human judgment, but on the strength of the organisational structures through which algorithmic outputs are interpreted, governed, and translated into sustainable athlete development pathways. Building on these limitations and future directions, the study concludes as follows.

Conclusion

In this sense, the AITIM Bridge Framework does not merely extend existing models of talent identification but redefines the conditions under which AI can be meaningfully integrated into elite sport systems, positioning governance, human interpretation, and organisational coherence as central determinants of sustainable athlete development.

Appendices

Appendix A. Search Logic Summary

Appendix A summarises the principal search logic in the review. Core search strings combined artificial intelligence terms (“Artificial Intelligence”, “Machine Learning”, “Computer Vision”, “Predictive Analytics”) with athlete pathway terms (“Talent Identification”, “Talent Development”, “Scouting”, “Academy Pathway”, “Athlete Retention”, “Player Progression”) and organisational terms (“Talent Management”, “Governance”, “Wellbeing”, “Transition”, “Organisational Support”). Searches were adapted to database-specific syntax while maintaining consistent conceptual blocks. Screening notes recorded whether each article contributed primarily to AI capability, talent system design, organisational integration, or athlete wellbeing and transition. This coding structure informed the subsequent thematic comparison and cross-study pattern analysis.

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