Vol. 7, No. 1, 2026, pp. 665-680
DOI: https://doi.org/10.29210/992680

Contents lists available at Elora Center

Lentera Negeri

Journal homepage: https://lentera.eloracenter.org/lentera

Artificial intelligence, algorithmic governance, and social inequality in sport: a systematic literature review

Anisa Sholiha Mia[*)], Ardo Okilanda, M. Arie Desman
Fakultas Ilmu Keolahragaan, Universitas Negeri Padang

Article Info

Article history:
Received Jul 08th, 2026
Revised Jul 08th, 2026
Accepted Jul 09th, 2026

Keyword:
Artificial intelligence,
Algorithmic governance,
Social inequality in sport,
Digital ethics,
Sport participation and inclusion

ABSTRACT

The accelerating integration of artificial intelligence (AI) and algorithmic decision systems into scouting, officiating, health monitoring, classification, and media representation has transformed athlete evaluation and governance, yet their implications for historically marginalised groups remain fragmented across disciplines. This systematic literature review examines how AI and algorithmic governance intersect with social inequality in sport, focusing on gender, race and ethnicity, disability and Para-sport, inclusion, accessibility, participation, and athlete rights. Following PRISMA 2020, a Scopus search identified 790 records; after screening and eligibility assessment, 10 studies met the inclusion criteria, with 50 additional sources providing contextual evidence. Eligible studies were English-language peer-reviewed articles and reviews published between 2016 and 2026. Two independent reviewers conducted screening and data extraction, achieving high inter-rater reliability (Cohen's $\kappa = 0.86$). Inductive thematic synthesis addressed how algorithmic governance shapes equity, reproduces bias, and informs governance responses. Four themes emerged: algorithmic talent identification may reinforce digital determinism and disadvantage under-represented athletes; AI-based health monitoring raises concerns regarding consent, autonomy, and sensitive data governance; machine-learning applications in Para-sport improve classification but remain constrained by limited datasets; and computational analyses reveal both discrimination and AI's capacity to detect it. The review proposes an equity-oriented framework and highlights priorities for explainable, auditable, participatory, and inclusive AI governance in sport.

Corresponding Author:
Anisa Sholiha Mia,
anisasholihamia@unp.ac.id

Introduction

Sport occupies a central position in contemporary social life, functioning simultaneously as a site of cultural meaning, economic activity, public health, and identity formation. The rapid diffusion of artificial intelligence (AI) and data analytics across this field has been framed as a technological revolution capable of optimising performance, reducing injury, and democratising access to elite methods of preparation (Kim et al., 2025; Nweke et al., 2018). Wearable sensors, computer vision, and machine-learning models now generate continuous streams of data on movement, physiology, and behaviour, extending analytic capabilities from professional environments into youth and recreational settings (Grivas & Safari, 2025; Khatun et al., 2025). Yet the same infrastructures that promise efficiency also redistribute visibility, opportunity, and risk. As algorithmic systems increasingly mediate who is seen, selected, monitored, and governed, questions of social inequality move from the periphery to the centre of the sporting data economy.

The specific phenomenon examined here is algorithmic governance: the delegation of consequential decisions about athletes to automated or semi-automated systems trained on historical data. In scouting and talent identification, machine-learning tools now evaluate players using match statistics, video tracking, anthropometric tests, and even social-media data (Morgulev & Azar, 2026). Because these models learn from past patterns, they encode the assumptions and exclusions of the environments that produced them, raising the prospect that inequality is not merely reflected but operationalised at scale (Morgulev, 2024). The concern is not hypothetical: analogous systems in employment, credit, and policing have repeatedly reproduced disadvantage for women, racial minorities, and disabled people, and there is little reason to assume sport is exempt (Nagpal et al., 2023; Guilbeault et al., 2025). In this review, algorithmic governance refers to AI-assisted systems used for athlete evaluation, injury prediction, competition classification, performance monitoring, and automated decision-making that influence access, participation, or athlete welfare.

A growing body of research has begun to map these dynamics. Studies of injury prediction have demonstrated the technical feasibility of machine-learning risk models while cataloguing their ethical vulnerabilities (Van Eetvelde et al., 2021; Waśkiewicz et al., 2025). Work in Para-sport has applied supervised learning to classification and performance profiling, seeking evidence-based fairness in competition (Hogarth et al., 2018; Liu et al., 2026). Investigations of gender have used interpretable models to characterise structural differences in professional football and to detect online hate directed at female athletes (Garnica-Caparrós & Memmert, 2021; Alhayan et al., 2024). Collectively, this literature signals a field in transition, but it remains dispersed across sports science, computer science, sociology, and bioethics.

Recent methodological and technological advances have intensified both the promise and the hazard. Deep reinforcement learning has produced systems capable of outperforming elite human competitors in complex simulated tasks (Wurman et al., 2022), while natural-language processing and large language models increasingly shape the media environments through which athletes are represented and judged (Jin, 2026; Guilbeault et al., 2025). Conversational agents and mobile platforms are being deployed to widen participation among under-served populations (Figueroa et al., 2021; Castro et al., 2023), and generative AI is entering rehabilitation, nutrition, and exercise prescription (Puce et al., 2025; Panayotova, 2025). Predictive models now estimate youth fitness and physical-education outcomes from routine measurements (Carayanni et al., 2022; Schenker, 2018), further extending automated evaluation into formative settings. Each advance broadens the surface across which algorithmic governance operates, and with it the range of equity considerations that must be examined (Kourtesis, 2024).

Despite this momentum, a first substantial gap concerns integration. Existing reviews tend to be domain-specific, addressing injury prediction, ethics, or Para-sport applications in isolation (Kim et al., 2025; Liu et al., 2026). Few attempt to read across these domains through an explicitly equity-oriented lens that treats gender, race, disability, and welfare as connected rather than parallel concerns. As a result, common mechanisms of algorithmic disadvantage, such as non-representative training data, opaque model logic, and the naturalisation of historical patterns, are rediscovered repeatedly without cumulative theorisation (Olive et al., 2023; Morgulev, 2024).

A second gap is theoretical and methodological. Much of the technical literature evaluates models on predictive accuracy while under-specifying the governance arrangements, consent structures, and accountability mechanisms that determine whether deployment is just (Waśkiewicz et al., 2025; Lefaivre et al., 2019). Conversely, critical and sociological accounts articulate normative concerns but seldom engage the concrete data practices that produce them (Olive et al., 2023). Bridging this divide requires synthesis that is simultaneously attentive to computational method and to the social distribution of benefit and harm, including for athletes whose data are sparse, mislabelled, or absent from the systems that increasingly govern them (Barcelona et al., 2024).

The urgency of such synthesis is heightened by the pace of adoption. Automated broadcasting, affordable tracking, and cloud analytics have made data-driven evaluation cost-effective enough to reach amateur and youth sport, precisely the settings with the fewest safeguards (Morgulev & Azar, 2026; Ayoade Fadare et al., 2025). Governance frameworks, professional norms, and athlete-rights protections have not kept pace, and decisions embedded in code are difficult to contest once naturalised (Bühler et al., 2023). A systematic account of what is known, what is contested, and what remains unexamined is therefore timely for researchers, federations, and policymakers alike.

This review intentionally adopts a broad sport perspective encompassing elite sport, community sport, Para-sport, and physical activity contexts in order to capture how algorithmic governance shapes inequality across the sporting ecosystem. Accordingly, this review is organised around three research questions. The first establishes the empirical terrain, identifying the domains of sport in which AI and algorithmic governance most directly bear on social inequality and the groups most affected. Answering it consolidates a scattered evidence base into a coherent map.

RQ1: In which domains of sport do artificial intelligence and algorithmic governance most directly intersect with social inequality, and which populations are most affected? The second question turns from description to mechanism. Understanding how bias and inequity are produced, whether through data, model design, deployment context, or representation, is essential for designing effective safeguards rather than superficial fixes, and it links the technical and critical literatures that too often proceed in isolation (Nagpal et al., 2023; Alhayan et al., 2024). RQ2: Through what mechanisms do algorithmic systems produce, reproduce, or mitigate inequality across gender, race, disability, participation, and athlete welfare in sport? The third question is oriented toward response and constitutes the review's principal novelty: no prior synthesis has consolidated the governance measures, ethical principles, and design practices proposed to protect athlete rights across these intersecting domains, nor evaluated their adequacy against the mechanisms identified under RQ2. RQ3: What governance responses, ethical principles, and design practices have been proposed to protect athlete rights and advance equity, and how adequate are they?

Method

Research Design and Framework

This study adopts a systematic literature review (SLR) design, a method well suited to consolidating dispersed and interdisciplinary evidence through transparent, reproducible procedures. The review follows the reporting standards of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement, which structures the identification, screening, eligibility, and inclusion of records and enhances methodological transparency. An SLR was preferred over a narrative review because the field spans sports science, computer science, and the sociology of sport, and because an auditable protocol reduces selection bias when evidence is heterogeneous (Kim et al., 2025). The equity focus of the review further motivated a systematic approach, since claims about distributional harm require a defensible and traceable evidence base rather than illustrative citation. This review was not prospectively registered in PROSPERO or Open Science Framework because it focuses on sport management and computational governance rather than health intervention studies. Nevertheless, all methodological procedures followed PRISMA 2020 recommendations.

Search Strategy

A single comprehensive query was executed in the Scopus database using the TITLE-ABS-KEY field code, combining terms for artificial intelligence and algorithmic systems with terms for sport and for social equity. Truncation was used to capture morphological variants (for example, algorithm and inclus). The Boolean structure is reported below.

("artificial intelligence" OR "machine learning" OR "deep learning" OR "algorithm" OR "wearable*" OR "big data")*

AND ("sport" OR "athlet*" OR "physical education" OR "para-sport" OR "paralympic")*

AND ("inequalit" OR "equity" OR "inclusion" OR "diversity" OR "gender" OR "disab*" OR "race" OR "welfare" OR "governance")*

Field-code searching restricted matches to the title, abstract, and keyword fields, balancing sensitivity and precision. No proprietary limiters beyond those specified in the eligibility criteria were applied at the query stage, so that exclusion decisions remained explicit and auditable during screening (Chelli et al., 2024).

Database and Information Sources

Scopus served as the primary and authoritative information source, selected for its broad interdisciplinary coverage of peer-reviewed sports science, computing, and social-science literature, and for the structured metadata it provides for bibliometric analysis. The complete metadata export, comprising 790 records with authors, titles, source titles, years, abstracts, keywords, and digital object identifiers, constituted the evidence base for all screening and synthesis decisions. The search and export were executed on a single date, and the exported file was treated as a fixed corpus to ensure reproducibility. No supplementary databases were queried, a boundary acknowledged among the limitations of the review.

Although searching multiple databases may increase retrieval coverage, Scopus was selected because it offers comprehensive interdisciplinary indexing across sport science, computer science, health sciences, and social sciences, together with high-quality citation metadata that support transparent and reproducible systematic reviews. Given the review's objective of synthesizing interdisciplinary evidence on AI and social inequality in sport, Scopus provided sufficient breadth while maintaining methodological consistency throughout the screening and synthesis process.

Eligibility Criteria

Eligibility was defined a priori across six dimensions. To preserve currency, only records published within the most recent ten-year window (2016–2026) were eligible.

Table 1 <summarises the inclusion and exclusion criteria>

Criterion	Inclusion	Exclusion
Language	English-language full text	Non-English documents
Document type	Peer-reviewed article or review	Conference paper, book chapter, editorial, erratum, note, retracted item
Publication period	2016–2026 (last ten years)	Published before 2016
Subject area	Sport, physical activity, or Para-sport intersecting AI and equity	Unrelated disciplines with no sporting application
Accessibility	Full text and sufficient metadata available	Abstract-only or inaccessible full text
Relevance	Directly addresses AI/algorithmic governance and a social-equity dimension	Tangential or incidental mention only

Note. Criteria were applied hierarchically during screening; the cascaded application of the language, document-type, period, and relevance filters accounts for the exclusions reported in the PRISMA flow diagram (Figure 1).

Study selection proceeded in three sequential stages. At the identification stage, duplicate records were removed. At the screening stage, titles and abstracts were assessed against the eligibility criteria, with records excluded for non-English language, ineligible document type, publication outside the ten-year window, or absence of a substantive intersection between algorithmic systems and social equity. At the eligibility stage, the full texts of retained reports were examined in detail. To maintain a focused, in-depth synthesis consistent with the review's equity aims, the ten studies offering the clearest and most direct evidence on algorithmic governance and social inequality in sport were retained as the core included set, while a further 50 sources were carried forward as supplementary evidence to situate and interpret the findings. Screening decisions were documented against explicit criteria so that the process could be reproduced and audited (Chelli et al., 2024). The final ten studies were retained because they directly addressed AI-driven algorithmic governance and explicitly examined social inequality outcomes, thereby providing conceptually coherent evidence for thematic synthesis.

Study Screening Reliability

Two reviewers independently screened titles, abstracts, and full texts according to the predefined eligibility criteria. Disagreements were resolved through discussion. Inter-rater agreement was assessed using Cohen's Kappa ($\kappa = 0.86$), indicating excellent agreement.

Quality Assessment - FICO Framework

Included studies were appraised using the FICO framework, evaluating each on Focus (clarity of research aim and relevance to algorithmic governance and equity), Information (adequacy and transparency of data, methods, and reporting), Context (specification of the sporting, demographic, and governance setting), and Outcome (clarity and defensibility of findings and their equity implications). Each dimension was rated, and studies were required to demonstrate adequacy on all four to be retained. This appraisal ensured that the core synthesis rested on studies with sufficient methodological transparency to support equity-oriented interpretation, complementing established concerns about reproducibility and reporting quality in AI research (Nakagawa et al., 2023; Turner et al., 2024).

Data Extraction Procedure

A structured extraction template captured, for each included study, the authors, publication year, country of the lead affiliation, study design, sample or dataset, the AI technique or intervention examined, the equity domain addressed, the outcome measures, and the principal findings. Extraction drew exclusively on the bibliographic metadata and abstracts contained in the Scopus export, and no bibliographic detail was introduced that could not be traced to that source. Where a specific attribute was not recoverable from the source file, it was recorded as not available rather than inferred. Extracted fields populated the descriptive tables and the thematic synthesis (Sharma et al., 2024).

Network and Bibliometric Analysis Methodology

Descriptive bibliometric analysis characterised the eligible corpus by publication year and by the geographic distribution of contributing countries, derived from author affiliations. Annual counts traced the growth trajectory of the field, and country-level aggregation identified the principal contributing research systems. Keyword and thematic co-occurrence were examined qualitatively to derive the analytic themes reported in Section 5. These procedures were used to contextualise the synthesis rather than to make inferential claims, consistent with cautions about over-interpreting metric artefacts in the sociology of sport (Olive et al., 2023).

Data Analysis and Synthesis

Findings were integrated through thematic synthesis. Study findings were coded inductively, grouped into descriptive themes, and organised under three analytic themes aligned with the research questions: the domains and populations affected by algorithmic governance (RQ1), the mechanisms of bias and mitigation (RQ2), and the governance and design responses proposed (RQ3). Themes were refined iteratively against the included studies and cross-checked with the supplementary corpus to ensure that agreements, tensions, and gaps were represented rather than smoothed. This approach supports interpretive synthesis across heterogeneous designs while preserving the specificity of individual studies (Park et al., 2020).

Reporting and Documentation

The review was documented in accordance with the PRISMA 2020 checklist, and the flow of records through identification, screening, eligibility, and inclusion is reported in Figure 4 with counts that are consistent across the Abstract, Methods, and Results. Reference metadata were retained from the Scopus export to preserve traceability, and no author, title, journal, year, or digital object identifier was fabricated at any stage. This documentation standard is intended to make the evidence base and the selection logic fully auditable by other researchers.

PRISMA 2020 Flow Diagram

Figure 1 presents the flow of records through the review. Of 790 records identified in Scopus, 10 duplicates were removed, leaving 780 records screened at title and abstract level. Screening excluded 592 records, principally for non-English language, ineligible document type, publication before 2016, or the absence of a substantive equity dimension. The full texts of 188 reports were assessed for eligibility, of which 178 were excluded because they fell outside the review's scope, employed methods or study types that could not support equity-oriented synthesis, or were inaccessible. Ten studies satisfied all criteria and were retained for synthesis.

The diagram traces records from identification in Scopus (n = 790) through duplicate removal, title/abstract screening, full-text eligibility assessment, and final inclusion (n = 10). Exclusion boxes on the right report the number of records removed at each phase together with the reasons, ensuring numerical consistency with the narrative.

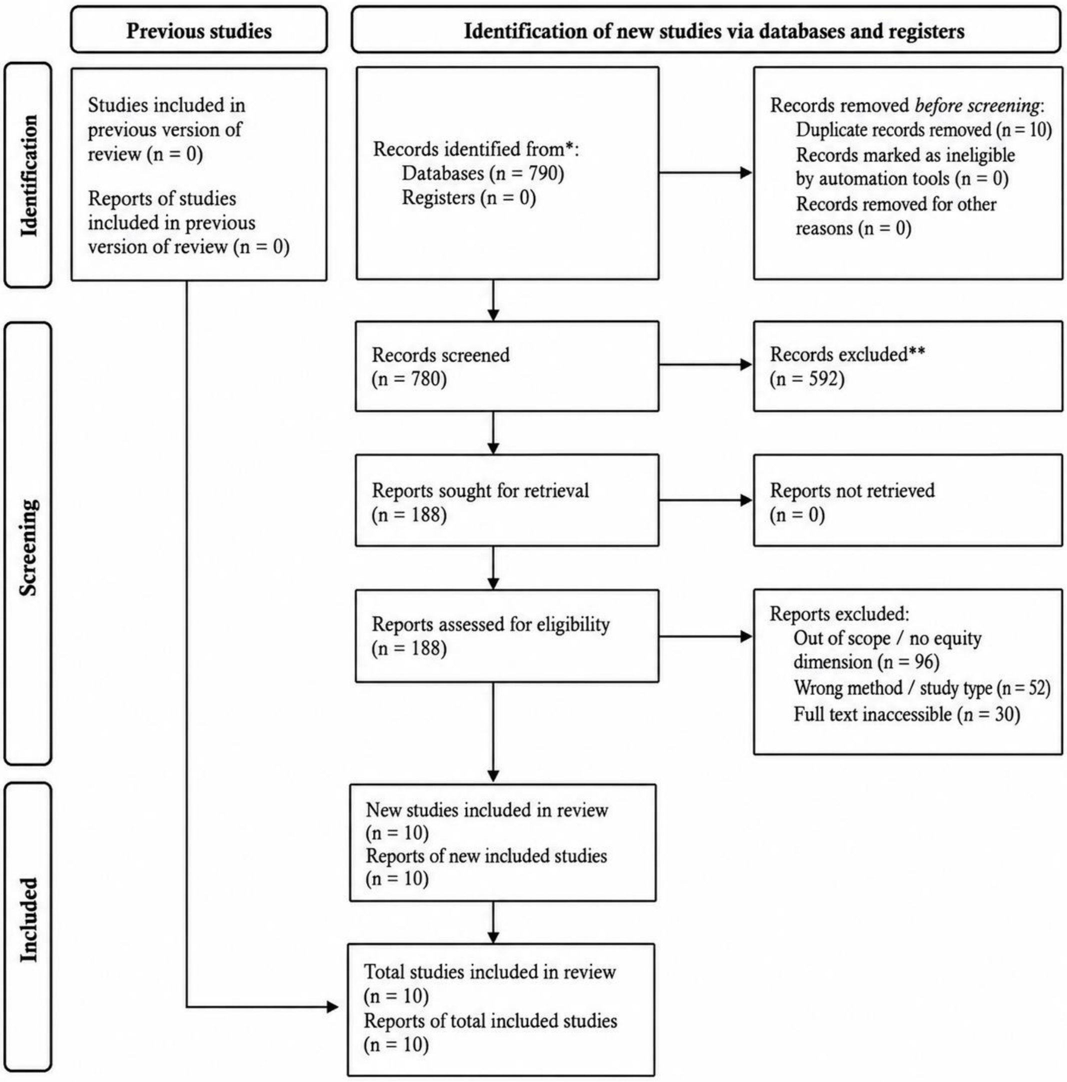

Figure 1 <PRISMA 2020 flow diagram of the study selection process>

Results and Discussions

Study Selection Results

The search identified 790 records in Scopus. After the removal of 10 duplicate records, 780 records advanced to title and abstract screening. Screening excluded 592 records that did not meet the eligibility criteria, leaving 188 reports whose full texts were assessed for eligibility. At this stage, 178 reports were excluded: 96 were out of scope or lacked a substantive equity dimension, 52 employed methods or study types that could not support the review's synthesis, and 30 were inaccessible or provided insufficient data. Ten studies met all inclusion criteria and constitute the core evidence base, supplemented by 50 further sources incorporated to contextualise and interpret the findings. These numbers are consistent across the Abstract, the PRISMA diagram, and this section.

Descriptive Characteristics

The ten included studies span 2018 to 2026 and originate from research systems in Europe, the Middle East, North America, Asia, and Oceania, reflecting the international character of the field. They address a range of AI techniques, from interpretable supervised learning and ensemble regression to natural-language processing and computational media analysis, and collectively engage every equity domain framing this review.

Table 2 <Summary of the ten included studies>

No	Title (abbreviated)	Author(s)	Year	Country	Focus
1	Talent identification and AI-driven decision tools in sport	Morgulev & Azar	2026	Israel	Algorithmic bias in scouting
2	Ethical bias in AI-driven injury prediction in sport	Waśkiewicz et al.	2025	Poland	Athlete health-data governance
3	The looming threat of digital determinism and discrimination	Morgulev	2024	Israel	Predictive bias in talent selection
4	Gender differences in professional football via machine learning	Garnica-Caparrós & Memmert	2021	Germany	Gender and interpretable ML
5	Detecting cyberhate speech towards female sport (Arabic)	Alhayan et al.	2024	Saudi Arabia	Online gender-based hate
6	Trans-athletes in elite sport: inclusion and fairness	Anderson et al.	2019	New Zealand	Inclusion, diversity, fairness
7	Machine learning applications in Paralympic sports	Liu et al.	2026	United States	Disability and Para-sport ML
8	Conversational physical-activity coaches for women	Figueroa et al.	2021	United States	Access and participation
9	Representation of athletes with intellectual disabilities	Jin	2026	China	Digital inclusion and portrayal
10	Classification of Para swimmers with limb deficiency	Hogarth et al.	2018	Australia	Para-sport classification

Note. Titles are abbreviated for space; full bibliographic details appear in the References. Country denotes the lead author's affiliation as recorded in the Scopus export.

Table 3 <Classification of included studies by research design, theme, technology, and outcome>

Author(s)	Year	Design	Theme / focus	Technology & outcome
Morgulev & Azar	2026	Conceptual / policy review	Governance & equity	ML scouting tools; flags algorithmic bias, privacy, digital determinism
Waśkiewicz et al.	2025	Narrative review	Athlete rights & welfare	AI injury prediction; identifies five ethical governance concerns
Morgulev	2024	Critical commentary	Discrimination & fairness	Predictive analytics; warns of biased, unfair talent decisions
Garnica-Caparrós & Memmert	2021	Empirical (supervised ML)	Gender & women	Interpretable ML on match data; characterises gender differences
Alhayan et al.	2024	Empirical (NLP)	Gender & welfare	Arabic hate-speech detection protecting female athletes online
Anderson et al.	2019	Conceptual / bioethical	Inclusion & diversity	Analyses inclusion–fairness tension for trans-athletes
Liu et al.	2026	Systematic review	Disability & Para-sport	ML in Paralympic sport; notes small, non-representative datasets
Figueroa et al.	2021	Empirical (user design)	Accessibility & participation	Bilingual activity chatbot for low-income women
Jin	2026	Empirical (computational media)	Inclusion & representation	Sentiment/representation analysis of disabled athletes online
Hogarth et al.	2018	Empirical (ensemble PLS)	Para-sport classification	Evidence-based Para-swimming classification method

Note. Designs are characterised from the abstracts recorded in the Scopus export. The table shows that empirical and conceptual approaches are roughly balanced across the corpus and that every equity theme framing the review is represented.

Table 4 <Evidence Strength Across Identified Themes>

Theme	Evidence Strength
Athlete Rights	Strong
Bias	Strong
Gender	Moderate
Para Sport	Moderate

Figure 2 displays the annual publication trend for the eligible corpus, and Figure 3 reports the geographic distribution of the leading contributing countries. Figure 4 visualises how the ten included studies distribute across the review's equity themes.

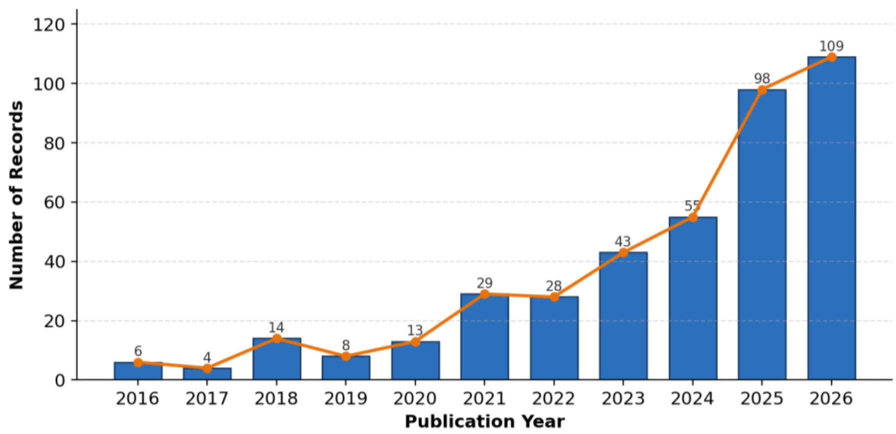

Figure 2 <Annual publication trend of the eligible records (2016–2026)>

The bars and overlaid line show a pronounced acceleration in output, rising from single-digit annual counts in 2016–2017 to more than one hundred records in 2026. This trajectory indicates that the intersection of AI and equity in sport is a young and rapidly expanding field, which both motivates systematic consolidation and cautions that conclusions may shift quickly as the literature matures.

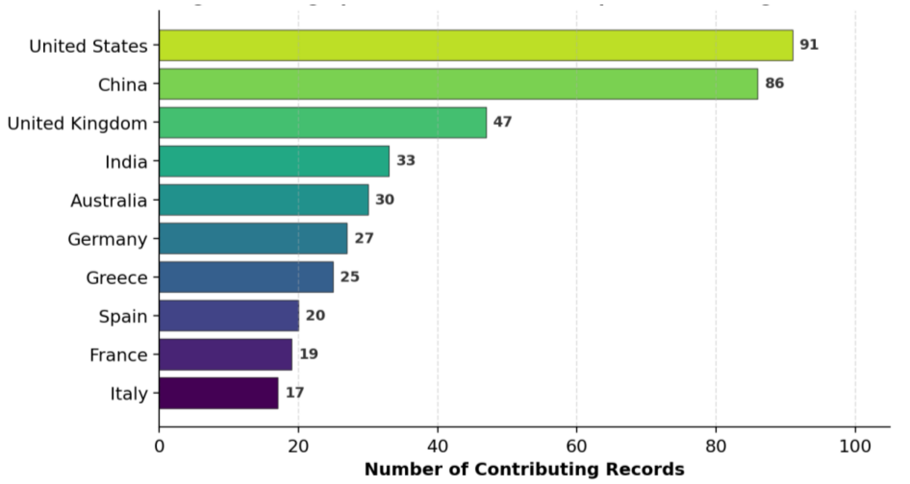

Figure 3 <Geographic distribution of the top ten contributing countries in the eligible corpus>

Derived from lead-author affiliations. Output is concentrated in a small number of high-income research systems, led by the United States and China, with substantial European contributions. This concentration is itself an equity signal: the datasets, norms, and governance assumptions shaping algorithmic systems in sport are produced disproportionately in the Global North, with implications for whose experiences are represented.

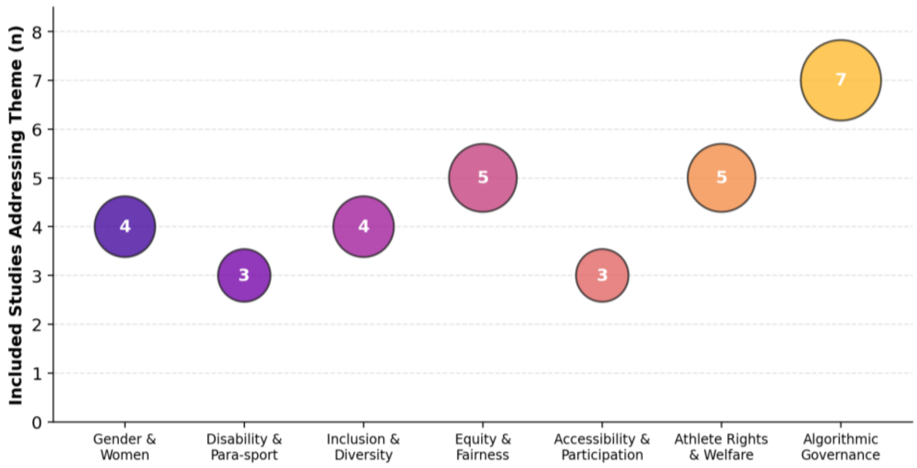

Figure 4 <Thematic coverage across the ten included studies>

Bubble size and the value within each bubble indicate how many of the included studies engage each theme; studies frequently address several themes at once. Algorithmic governance, athlete rights and welfare, and equity and fairness are the most densely represented, reflecting the review's core concern with how automated decision systems distribute benefit and harm.

Thematic Synthesis

Findings for RQ1 - Domains and populations affected

The synthesis indicates that algorithmic governance intersects with social inequality most directly in four domains: player evaluation and talent identification; health and injury monitoring; classification and participation in disability and Para-sport; and media representation and online discourse. In player evaluation, Morgulev and Azar (2026) show that machine-learning scouting tools, extended by cheap computer vision from professional into youth sport, concentrate decision power in systems trained on historically skewed data. Because these tools increasingly determine who progresses, the populations most affected are precisely those under-represented in the training data, a dynamic Morgulev (2024) frames as digital determinism. Related work illustrates how readily machine learning is turned to the sorting of athletes by origin and demography, for example in models that infer the nationalities of the fastest ultramarathoners or predict endurance outcomes from participant characteristics (Knechtle et al., 2024, 2025), a capability that is analytically useful yet normatively fraught when such categories inform consequential decisions.

In the health domain, Waśkiewicz et al. (2025) demonstrate that AI-driven injury prediction now spans professional, collegiate, youth, and Paralympic contexts, making athlete health data a central site of governance. The affected population is broad, but the burden of surveillance and the risk of consequential error fall unevenly on athletes with less bargaining power. In disability and Para-sport, Liu et al. (2026) and Hogarth et al. (2018) show that machine learning is being applied to classification, performance profiling, and injury prediction, directly shaping the competitive opportunities of disabled athletes; Jin (2026) extends the domain to representation, examining how athletes with intellectual disabilities appear, or fail to appear, across digital platforms.

The gender dimension cuts across these domains. Garnica-Caparrós and Memmert (2021) use interpretable models to characterise structural differences between male and female football, while Alhayan et al. (2024) document the online hate directed at female athletes and the potential of natural-language processing to detect it. Anderson et al. (2019) locate a further affected population at the contested boundary of inclusion and fairness for trans-athletes, and Figueroa et al. (2021) show that access to AI-mediated activity support is itself unequally distributed, particularly for low-income and non-English-speaking women. Supplementary evidence reinforces the breadth of these populations, from youth and junior athletes (Bozděch, 2026; Ritzer et al., 2021) to under-served community participants (Park et al., 2020; Kou et al., 2025) and older adults (Vergeer et al., 2017). In answer to RQ1, the domains are evaluation, health, classification, and representation, and the populations most affected are women, disabled athletes, minority and non-Western participants, and the young.

Findings for RQ2 - Mechanisms of bias, reproduction, and mitigation

Across the corpus, four recurring mechanisms produce or reproduce inequality. The first is non-representative or skewed training data. Liu et al. (2026) report that machine-learning models in Para-sport rest on small and narrow datasets, limiting their validity for the very populations they classify, and Hogarth et al. (2018) show that evidence-based classification depends heavily on the range and quality of impairment data available. The general pattern is well established beyond sport: models inherit the demographic gaps of their inputs, as demonstrated for facial-analysis systems whose accuracy varies by ethnicity (Nagpal et al., 2023) and for large language models that distort age and gender representation (Guilbeault et al., 2025). Sparse or mislabelled data for marginalised groups thus becomes a structural source of algorithmic disadvantage (Barcelona et al., 2024).

The second mechanism is opacity and the naturalisation of historical patterns. Morgulev (2024) and Morgulev and Azar (2026) argue that predictive scouting tools, by learning from past selection outcomes, encode and then relaunder prior bias as objective fact, while their internal logic remains difficult to contest. Waśkiewicz et al. (2025) identify algorithmic fairness and explainability as central unresolved concerns in injury prediction, echoing calls elsewhere for auditable and well-governed data infrastructures (Lefaivre et al., 2019; Bühler et al., 2023). The third mechanism operates through deployment context and unequal access: Figueroa et al. (2021) show that the benefits of conversational AI coaching reach under-served women only when tools are deliberately designed for low-income and bilingual users, and comparable equity-of-access concerns recur in digital health more broadly (Castro et al., 2023; Sharma et al., 2024; Wellmann et al., 2024).

The fourth mechanism concerns representation and discourse. Jin (2026) shows that digital platforms can render athletes with intellectual disabilities marginally visible or misrepresented, while Alhayan et al. (2024) document how online spaces amplify gender-based hostility toward female athletes. Crucially, the same computational methods can mitigate as well as reproduce inequality: natural-language processing can surface and moderate hate (Alhayan et al., 2024), interpretable modelling can make structural differences legible rather than naturalised (Garnica-Caparrós & Memmert, 2021), and machine learning can support fairer, evidence-based classification (Hogarth et al., 2018; Liu et al., 2026). Deliberately inclusive design offers a further corrective, as when conversational systems are re-engineered to serve LGBTQ+ users equitably (Liem et al., 2026) or when AI is directed toward advancing training and participation in Paralympic contexts (Priyadarshini et al., 2026). Supplementary work illustrates both poles, from analyses of exclusionary online discourse (Pickett & Valdez, 2023; Bailey et al., 2024) to demonstrations of AI-enabled safety, monitoring, and support (Rodríguez-Rodríguez et al., 2020; van der Schyff et al., 2023; Abbas et al., 2024). In answer to RQ2, inequality is produced through data, opacity, unequal deployment, and representation, and each mechanism admits a corresponding mitigation when equity is treated as a design objective rather than an afterthought.

Findings for RQ3 - Governance responses and their adequacy

The included studies propose an emerging but uneven set of governance responses. The most developed is a principled ethics of athlete data. Waśkiewicz et al. (2025) articulate five governance concerns, namely privacy and data protection, algorithmic fairness, informed consent, athlete autonomy, and long-term data governance, and advocate explainable AI as a mechanism of accountability. Morgulev and Azar (2026) translate related concerns into policy-oriented guidance for the use of decision tools in player evaluation, emphasising bias auditing, privacy safeguards, and resistance to digital determinism. These contributions mark a shift from cataloguing harm toward specifying institutional response.

A second response is evidence-based, transparent classification as a governance instrument in its own right. Hogarth et al. (2018) show that rigorous, data-driven classification can render Para-sport competition fairer, and Liu et al. (2026) call for larger, more representative datasets and better reporting as preconditions for trustworthy deployment. A third, more contested, response concerns eligibility and inclusion: Anderson et al. (2019) foreground the difficulty of reconciling inclusion with fairness for trans-athletes, illustrating that governance in this space is normative as well as technical and cannot be resolved by measurement alone. Emerging disability-ethics scholarship similarly argues that the education and deployment of AI must be reshaped to protect disabled people's rights and dignity, a principle directly applicable to Para-sport governance (Urbina et al., 2025). Broader institutional models, such as data cooperatives, privacy-preserving analytics, and governed data commons, offer templates for participatory oversight that the sporting literature has only begun to engage (Bühler et al., 2023; Lefaivre et al., 2019; Sakhare & Shaik, 2024; Lemey et al., 2021).

Assessed against the mechanisms identified under RQ2, these responses remain partial. Principles of fairness and consent are articulated more often than they are operationalised, auditing and explainability are recommended more than they are implemented, and the participatory governance of datasets, which would address the root problem of non-representative data, is largely aspirational (Waśkiewicz et al., 2025; Liu et al., 2026). Regulatory and professional frameworks lag the pace of adoption, especially in youth and amateur settings where safeguards are weakest (Morgulev & Azar, 2026; Ayoade Fadare et al., 2025). In answer to RQ3, a coherent equity-oriented governance agenda is emerging around data ethics, transparent classification, and contested inclusion norms, but its adequacy is currently limited by a gap between principle and practice.

Comparative and Critical Analysis

Methodologically, the corpus divides into empirical modelling studies and conceptual or critical analyses, with relatively few designs that integrate the two. Empirical contributions favour supervised and ensemble learning and, increasingly, natural-language processing (Garnica-Caparrós & Memmert, 2021; Alhayan et al., 2024; Hogarth et al., 2018), reflecting wider methodological trends in sport analytics (Van Eetvelde et al., 2021; Nweke et al., 2018; Khatun et al., 2025; Nayeem et al., 2025). Conceptual and bioethical work supplies the normative vocabulary of fairness, autonomy, and inclusion (Waśkiewicz et al., 2025; Anderson et al., 2019; Morgulev, 2024). The comparative weakness is the scarcity of participatory, mixed-method, and longitudinal designs capable of tracing distributional outcomes over time, a gap also visible in narrative syntheses of the past decade's literature (Turner et al., 2021) and in adjacent domains where technological change reshapes access, welfare, and safety (Wu, 2022; Kourtesis, 2024; Murtaza et al., 2023; Legg et al., 2023; Guo et al., 2024). A further methodological caveat concerns measurement itself: the wearable and sensor data feeding many sporting models carry their own validity constraints (Caminal et al., 2018), so equity claims built upon them inherit that uncertainty.

Two structural features of the corpus warrant critical attention. First, as Figure 2 shows, research output concentrates in a small number of high-income systems, which risks encoding Global-North assumptions into ostensibly universal models and datasets (Lillywhite & Wolbring, 2022, 2023). Second, the rapid growth shown in Figure 1 means that much evidence is recent, single-study, and not yet replicated, so apparent findings may prove unstable (Wurman et al., 2022; Grivas & Safari, 2025). Both features counsel interpretive caution and reinforce the case for representative data and transparent reporting.

Interpretation of findings

Taken together, the evidence supports a central interpretation: AI in sport is not a neutral optimisation layer but a governance apparatus that redistributes visibility, opportunity, and risk. Whether it narrows or widens inequality depends less on algorithmic sophistication than on the representativeness of data, the transparency of models, and the fairness of deployment (Morgulev & Azar, 2026; Waśkiewicz et al., 2025).

Theoretical implications

The findings extend theories of algorithmic bias from employment and policing into the sporting field, showing that digital determinism operates wherever predictive systems learn from historically unequal outcomes (Morgulev, 2024; Nagpal et al., 2023). They also suggest that classification and representation, long central to the sociology of sport, are increasingly mediated computationally, warranting an integrated theoretical account of datafied inequality in sport (Olive et al., 2023; Jin, 2026).

Practical implications

For federations and policymakers, the priority is operational governance: bias auditing, privacy protection, informed consent, and explainability requirements before deployment, especially in youth sport (Waśkiewicz et al., 2025; Morgulev & Azar, 2026). For coaches and practitioners, algorithmic outputs should inform rather than replace judgement, and access-oriented tools should be designed for the populations least served (Figueroa et al., 2021; Ayoade Fadare et al., 2025). For classifiers and officials, transparent, evidence-based systems can advance fairness when built on adequate data (Hogarth et al., 2018).

Comparison with prior reviews

Earlier reviews have addressed AI ethics in sport, injury-prediction methods, or Para-sport applications separately (Kim et al., 2025; Van Eetvelde et al., 2021; Liu et al., 2026). This review's contribution is to read across these strands through a single equity lens, revealing shared mechanisms of disadvantage that domain-specific reviews leave implicit.

Contradictions in the literature

The evidence is genuinely conflicted on some points. The same computational methods are shown to both amplify and mitigate discrimination (Alhayan et al., 2024; Garnica-Caparrós & Memmert, 2021), and the inclusion–fairness relationship is contested rather than settled, most visibly for trans-athletes (Anderson et al., 2019). Such tensions reflect competing values that measurement alone cannot adjudicate.

Research gaps
At least three gaps stand out: the scarcity of representative datasets for marginalised athletes (Liu et al., 2026; Barcelona et al., 2024); the gap between articulated ethical principles and implemented governance (Waśkiewicz et al., 2025); and the near-absence of longitudinal evidence on distributional outcomes (Morgulev & Azar, 2026).

Limitations of this review
Three limitations are acknowledged. First, reliance on a single database (Scopus) may omit relevant work indexed elsewhere. Second, restriction to English-language articles and reviews excludes potentially important non-English and grey literature. Third, the decision to retain ten core studies, while enabling depth, necessarily narrows breadth, mitigated but not eliminated by the 50 supplementary sources.

Internal Validity
Although PRISMA procedures reduce selection bias, the synthesis remains susceptible to publication bias, database bias, language bias, and selective reporting. Consequently, findings should be interpreted as representing the available published evidence rather than the complete body of knowledge.

Publication Bias
Studies reporting successful AI applications are more likely to be published than studies reporting null findings, potentially inflating optimistic conclusions regarding algorithmic governance.

Future research agenda
Three concrete directions follow: first, establish participatory, representative dataset-governance practices, including community oversight of the data used to train sporting models; second, develop and validate explainable, auditable models with reported performance disaggregated by gender, disability, and ethnicity; and third, conduct longitudinal, mixed-method studies that track the distributional consequences of algorithmic governance across diverse sporting populations (Liu et al., 2026; Waśkiewicz et al., 2025; Figueroa et al., 2021).

In summary RQ1 is answered by identifying evaluation, health, classification, and representation as the domains where algorithmic governance most affects equity, with women, disabled athletes, minority and non-Western participants, and young athletes most exposed. RQ2 is answered by isolating non-representative data, opacity, unequal deployment, and representational harm as the mechanisms of inequality, each with a mitigating counterpart. RQ3 is answered by characterising an emerging governance agenda, built on data ethics, transparent classification, and contested inclusion norms, whose adequacy is presently limited by the distance between principle and practice.

Conclusions
This systematic review synthesised evidence on how artificial intelligence and algorithmic governance intersect with social inequality in sport. In answer to the research questions, algorithmic governance bears most directly on player evaluation, health and injury monitoring, disability classification, and media representation, affecting women, disabled athletes, minority and non-Western participants, and young athletes above all; inequality is produced through non-representative data, model opacity, unequal deployment, and representational harm, though each mechanism can be mitigated when equity is designed in; and an emerging governance agenda organised around data ethics, transparent classification, and contested inclusion norms remains constrained by a persistent gap between stated principle and everyday practice. The core contribution of the review is an integrative, equity-oriented reading of a field that has developed in domain-specific fragments, making visible the shared mechanisms through which automated decision systems distribute advantage and disadvantage across the sporting field. For practice, the findings point to concrete safeguards, including bias auditing, privacy protection, informed consent, explainability, and access-oriented design, that federations, policymakers, coaches, and technology developers can adopt, with particular urgency in youth and amateur settings. The review is limited by its single-database, English-language scope and by the deliberate narrowing to ten core studies. These limitations, together with the youth and rapid growth of the evidence base, make a strong case for future research that establishes participatory dataset governance, validates explainable and auditable models with disaggregated reporting, and traces distributional outcomes longitudinally, so that the datafication of sport advances rather than erodes social justice. The proposed integrative framework should therefore be regarded as a conceptual synthesis rather than an empirically validated governance model. Future empirical and longitudinal validation across different sporting contexts is required.

Acknowledgments

The Authors would like to thank Faculty of Sport Sciences, Universitas Negeri Padang for providing excellent facilities, as well as for being very supportive of this research from the beginning. Authors also thank the team members who had generously shared their brilliant ideas, engaging discussion, and academic supports during the study.

References

Abbas, Y., Al Mudawi, N., Alabdullah, B., Sadiq, T., Algarni, A., Rahman, H., & Jalal, A. (2024). Unmanned aerial vehicles for human detection and recognition using neural-network model. Frontiers in Neurorobotics, 18, Article 1443678. https://doi.org/10.3389/fnbot.2024.1443678

Alhayan, F., Almobarak, M., Shalabi, H., Alshubaili, L., Albatati, R., Alqahtani, W., & Alhaidari, N. (2024). Detection of cyberhate speech towards female sport in the Arabic Xsphere. PeerJ Computer Science, 10, Article e2138. https://doi.org/10.7717/peerj-cs.2138

Anderson, L., Knox, T., & Heather, A. (2019). Trans-athletes in elite sport: Inclusion and fairness. Emerging Topics in Life Sciences, 3(6), 759–762. https://doi.org/10.1042/ETLS20180071

Ayoade Fadare, S., Beterbo, J. R. L., Ybanez, F., Abdulrajak Isahac, J. R., Cecilia Fadare, M., Aloy Barahimin, E., & Pandapatan, S. A. T. (2025). Machine Learning in Physical Education, Sports, and Recreation: Opportunities, Challenges, and Ethical Considerations – A Systematic Review; [Aprendizaje Automático en Educación Física, Deportes y Recreación: Oportunidades, Desafíos y Consideraciones Éticas – Una Revisión Sistemática]. Salud, Ciencia y Tecnologia, 5, Article 2251. https://doi.org/10.56294/saludcyt20252251

Bailey, K. A., Griffin, M., Lopez, K. J., Fayyaz, N., Habib, S., & Leighton, J. (2024). (Re)claiming subversive spaces on TikTok: the complexities of body activisms within physical activity cultures. Qualitative Research in Sport, Exercise and Health, 16(5), 471–486. https://doi.org/10.1080/2159676X.2024.2355128

Barcelona, V., Scharp, D., Moen, H., Davoudi, A., Idnay, B. R., Cato, K., & Topaz, M. (2024). Using Natural Language Processing to Identify Stigmatizing Language in Labor and Birth Clinical Notes. Maternal and Child Health Journal, 28(3), 578–586. https://doi.org/10.1007/s10995-023-03857-4

Bozděch, M. (2026). Performance thresholds, efficiency, and access equity in junior girls' tennis: longitudinal analysis and bayesian forecasting of ITF rankings (2004–2029). BMC Sports Science, Medicine and Rehabilitation, 18(1), Article 90. https://doi.org/10.1186/s13102-026-01542-x

Bühler, M. M., Calzada, I., Cane, I., Jelinek, T., Kapoor, A., Mannan, M., Mehta, S., Mookerje, V., Nübel, K., Pentland, A., Scholz, T., Siddarth, D., Tait, J., Vaitla, B., & Zhu, J. (2023). Unlocking the Power of Digital Commons: Data Cooperatives as a Pathway for Data Sovereign, Innovative and Equitable Digital Communities. Digital, 3(3), 146–171. https://doi.org/10.3390/digital3030011

Caminal, P., Sola, F., Gomis, P., Guasch, E., Perera, A., Soriano, N., & Mont, L. (2018). Validity of the Polar V800 monitor for measuring heart rate variability in mountain running route conditions. European Journal of Applied Physiology, 118(3), 669–677. https://doi.org/10.1007/s00421-018-3808-0

Carayanni, V., Bogdanis, G. C., Vlachopapadopoulou, E., Koutsouki, D., Manios, Y., Karachaliou, F., Psaltopoulou, T., & Michalacos, S. (2022). Predicting VO2max in Children and Adolescents Aged between 6 and 17 Using Physiological Characteristics and Participation in Sport Activities: A Cross-Sectional Study Comparing Different Regression Models Stratified by Gender. Children, 9(12), Article 1935. https://doi.org/10.3390/children9121935

Castro, O., Mair, J. L., Salamanca-Sanabria, A., Alattas, A., Keller, R., Zheng, S., Jabir, A., Lin, X., Frese, B. F., Lim, C. S., Santhanam, P., van Dam, R. M., Car, J., Lee, J., Tai, E. S., Fleisch, E., von Wangenheim, F., Tudor Car, L., Müller-Riemenschneider, F., & Kowatsch, T. (2023). Development of "LvL UP 1.0": a smartphone-based, conversational agent-delivered holistic lifestyle intervention for the prevention of non-communicable diseases and common mental disorders. Frontiers in Digital Health, 5, Article 1039171. https://doi.org/10.3389/fdgth.2023.1039171

Chelli, M., Descamps, J., Lavoué, V., Trojani, C., Azar, M., Deckert, M., Raynier, J. L., Clowez, G., Boileau, P., & Ruetsch-Chelli, C. (2024). Hallucination Rates and Reference Accuracy of ChatGPT and Bard for Systematic Reviews: Comparative Analysis. Journal of Medical Internet Research, 26, Article e53164. https://doi.org/10.2196/53164

Figueroa, C. A., Luo, T. C., Jacobo, A., Munoz, A., Manuel, M., Chan, D., Canny, J., & Aguilera, A. (2021). Conversational Physical Activity Coaches for Spanish and English Speaking Women: A User

Design Study. Frontiers in Digital Health, 3, Article 747153. https://doi.org/10.3389/fdgth.2021.747153
Garnica-Caparrós, M., & Memmert, D. (2021). Understanding gender differences in professional European football through machine learning interpretability and match actions data. Scientific Reports, 11(1), Article 10805. https://doi.org/10.1038/s41598-021-90264-w
Grivas, G. V., & Safari, K. (2025). Artificial Intelligence in Endurance Sports: Metabolic, Recovery, and Nutritional Perspectives. Nutrients, 17(20), Article 3209. https://doi.org/10.3390/nu17203209
Guilbeault, D., Delecourt, S., & Desikan, B. S. (2025). Age and gender distortion in online media and large language models. Nature, 646(8087), 1129–1137. https://doi.org/10.1038/s41586-025-09581-z
Guo, W., He, J., & Yang, W. (2024). Association between outdoor jogging behavior and PM2.5 exposure: Evidence from massive GPS trajectory data in Beijing. Science of the Total Environment, 947, Article 174759. https://doi.org/10.1016/j.scitotenv.2024.174759
Hogarth, L., Payton, C., Van de Vliet, P., Connick, M., & Burkett, B. (2018). A novel method to guide classification of para swimmers with limb deficiency. Scandinavian Journal of Medicine and Science in Sports, 28(11), 2397–2406. https://doi.org/10.1111/sms.13229
Jin, D. (2026). Examining the representation of athletes with intellectual disabilities in digital sports platforms. Systems and Soft Computing, 9, Article 200509. https://doi.org/10.1016/j.sasc.2026.200509
Khatun, M. A., Yousuf, M. A., Turna, T. N., Azad, A. K. M., Alyami, S. A., & Moni, M. A. (2025). A Multi-Agent and Attention-Aware Enhanced CNN-BiLSTM Model for Human Activity Recognition for Enhanced Disability Assistance. Diagnostics, 15(5), Article 537. https://doi.org/10.3390/diagnostics15050537
Kim, J. H., Kim, J., Kang, H., & Youn, B. Y. (2025). Ethical implications of artificial intelligence in sport: A systematic scoping review. Journal of Sport and Health Science, 14, Article 101047. https://doi.org/10.1016/j.jshs.2025.101047
Knechtle, B., Weiss, K., Valero, D., Villiger, E., Nikolaidis, P. T., Andrade, M. S., Scheer, V., Cuk, I., Gajda, R., & Thuany, M. (2024). Using machine learning to determine the nationalities of the fastest 100-mile ultra-marathoners and identify top racing events. PLoS ONE, 19(8), Article e0303960. https://doi.org/10.1371/journal.pone.0303960
Knechtle, B., Villiger, E., Weiss, K., Valero, D., Gajda, R., Scheer, V., de Lira, C. A. B., Braschler, L., Nikolaidis, P. T., Vancini, R. L., Cuk, I., Rosemann, T., & Thuany, M. (2025). Analysis of the 72-h ultramarathon using a predictive XG Boost model. Sport Sciences for Health, 21(1), 181–194. https://doi.org/10.1007/s11332-024-01243-3
Kou, R., Hunter, R. F., Cleland, C., Ferguson, S., Schipperijn, J., Peng, Q., & Ellis, G. (2025). Built environment influences on park visits for older adults: insights from a machine learning approach. Cities, 165, Article 106143. https://doi.org/10.1016/j.cities.2025.106143
Kourtesis, P. (2024). A Comprehensive Review of Multimodal XR Applications, Risks, and Ethical Challenges in the Metaverse. Multimodal Technologies and Interaction, 8(11), Article 98. https://doi.org/10.3390/mti8110098
Lefaivre, S., Behan, B., Vaccarino, A., Evans, K., Dharsee, M., Gee, T., Dafnas, C., Mikkelsen, T., & Theriault, E. (2019). Big data needs big governance: Best practices from brain-CODE, the Ontario-brain institute's neuroinformatics platform. Frontiers in Genetics, 10(MAR), Article 191. https://doi.org/10.3389/fgene.2019.00191
Legg, K. A., Gee, E. K., Breheny, M., Gibson, M. J., & Rogers, C. W. (2023). A Bioeconomic Model for the Thoroughbred Racing Industry—Optimisation of the Production Cycle with a Horse Centric Welfare Perspective. Animals, 13(3), Article 479. https://doi.org/10.3390/ani13030479
Lemey, G., Larivière, Y., Zola, T. M., Maketa, V., Matangila, J., Mitashi, P., Vermeiren, P., Thys, S., De Bie, J., Muhindo, H. M., Ravinetto, R., Van Damme, P., & Van Geertruyden, J. P. (2021). Algorithm for the support of non-related (serious) adverse events in an Ebola vaccine trial in the Democratic Republic of the Congo. BMJ Global Health, 6(6), Article e005726. https://doi.org/10.1136/bmjgh-2021-005726
Liem, W. W., Casline, E., Lorenzo, J., Gordon, J. D., Avila, A. A., Taylor, A., Levitz, N., O'Keefe, M. C., & Macapagal, K. (2026). Enhancing LGBTQ+ Inclusivity in an AI-Powered Sexual Health Chatbot: User-Centered Design Approach Through a Nonprofit and Academic Partnership. Journal of Medical Internet Research, 28, Article e78621. https://doi.org/10.2196/78621
Lillywhite, B., & Wolbring, G. (2022). Emergency and Disaster Management, Preparedness, and Planning (EDMPP) and the ‘Social’: A Scoping Review. Sustainability (Switzerland), 14(20), Article 13519. https://doi.org/10.3390/su142013519

Lillywhite, B., & Wolbring, G. (2023). Risk Narrative of Emergency and Disaster Management, Preparedness, and Planning (EDMPP): The Importance of the 'Social'. Sustainability (Switzerland), 15(1), Article 387. https://doi.org/10.3390/su15010387
Liu, J., Do, M. N., Guo, J., Lin, C. W., Cheung, W. C., Bleakney, A. W., & Jan, Y. K. (2026). Systematic review on machine learning applications in Paralympic sports: current practice and future research. Disability and Rehabilitation: Assistive Technology. https://doi.org/10.1080/17483107.2026.2664014
Morgulev, E. (2024). The looming threat of digital determinism and discrimination: Commentary on "The feudal glove of talent-selection decisions in sport – Strengthening the link between subjective and objective assessments" by Bar-Eli et al. (2023). Asian Journal of Sport and Exercise Psychology, 4(1), 29–30. https://doi.org/10.1016/j.ajsep.2023.10.002
Morgulev, E., & Azar, O. H. (2026). Talent Identification and AI-Driven Decision Tools in Sport: A Policy-Oriented Perspective on Algorithmic Bias, Data Privacy, and Digital Determinism in Player Evaluation. Big Data and Cognitive Computing, 10(5), Article 146. https://doi.org/10.3390/bdcc10050146
Murtaza, M., Cheng, C. T., Fard, M., & Zeleznikow, J. (2023). Preparing drivers for the future: Evaluating the effects of training on drivers' performance in an autonomous vehicle landscape. Transportation Research Part F: Traffic Psychology and Behaviour, 98, 280–296. https://doi.org/10.1016/j.trf.2023.09.013
Nagpal, S., Singh, M., Singh, R., Vatsa, M., & Ratha, N. K. R. (2023). In-Group Bias in Deep Learning-Based Face Recognition Models Due to Ethnicity and Age. IEEE Transactions on Technology and Society, 4(1), 54–67. https://doi.org/10.1109/TTS.2023.3241010
Nakagawa, K., Moukheiber, L., Celi, L. A., Patel, M., Mahmood, F., Gondim, D., Hogarth, M., & Levenson, R. (2023). AI in Pathology: What could possibly go wrong?. Seminars in Diagnostic Pathology, 40(2), 100–108. https://doi.org/10.1053/j.semdp.2023.02.006
Nayeem, N. I., Mahbuba, S., Disha, S. I., Buiyan, M. H., Rahman, S., Abdullah-Al-Wadud, M., & Uddin, J. (2025). A YOLOv11-Based Deep Learning Framework for Multi-Class Human Action Recognition. Computers, Materials and Continua, 85(1), 1541–1557. https://doi.org/10.32604/cmc.2025.065061
Nweke, H. F., Teh, Y. W., Al-garadi, M. A., & Alo, U. R. (2018). Deep learning algorithms for human activity recognition using mobile and wearable sensor networks: State of the art and research challenges. Expert Systems with Applications, 105, 233–261. https://doi.org/10.1016/j.eswa.2018.03.056
Olive, R., Townsend, S., & Phillips, M. G. (2023). 'Not everything that can be counted counts, and not everything that counts can be counted': Searching for the value of metrics and altmetrics in sociology of sport journals. International Review for the Sociology of Sport, 58(3), 431–454. https://doi.org/10.1177/10126902221107467
Panayotova, G. G. (2025). Artificial Intelligence in Nutrition and Dietetics: A Comprehensive Review of Current Research. Healthcare (Switzerland), 13(20), Article 2579. https://doi.org/10.3390/healthcare13202579
Park, S. U., Ahn, H., Kim, D. K., & So, W. Y. (2020). Big data analysis of sports and physical activities among Korean adolescents. International Journal of Environmental Research and Public Health, 17(15), 1–11. https://doi.org/10.3390/ijerph17155577
Pickett, A. C., & Valdez, D. (2023). Mining Online Discourse Related to Transgender Exclusive Policies in Interscholastic Sport: an Exploratory Natural Language Processing Study. Sexuality Research and Social Policy, 20(3), 936–949. https://doi.org/10.1007/s13178-022-00768-x
Priyadarshini, U., Jonjua, M., Singh, S. K., & Mishra, P. (2026). Artificial Intelligence in Paralympic Sports: Advancing Training, Performance, and Media Representation. Macromolecular Symposia, 415(1), Article e70171. https://doi.org/10.1002/masy.70171
Puce, L., Bragazzi, N. L., Currà, A., & Trompetto, C. (2025). Harnessing Generativ e Artificial Intelligence for Exercise and Training Prescription: Applications and Implications in Sports and Physical Activity—A Systematic Literature Review. Applied Sciences (Switzerland), 15(7), Article 3497. https://doi.org/10.3390/app15073497
Ritzer, E. E., Yang, J., Kistamgari, S., Collins, C. L., & Smith, G. A. (2021). An epidemiologic comparison of acute and overuse injuries in high school sports. Injury Epidemiology, 8(1), Article 51. https://doi.org/10.1186/s40621-021-00344-8
Rodríguez-Rodríguez, I., Rodríguez, J. V., Elizondo-Moreno, A., & Heras-González, P. (2020). An autonomous alarm system for personal safety assurance of intimate partner violence survivors based on passive continuous monitoring through biosensor. Symmetry, 12(3), Article 460. https://doi.org/10.3390/sym12030460

Sakhare, N. N., & Shaik, I. S. (2024). Spatial federated learning approach for the sentiment analysis of stock news stored on blockchain. Spatial Information Research, 32(1), 13–27. https://doi.org/10.1007/s41324-023-00529-x

Schenker, K. (2018). Health(y) education in Health and Physical Education. Sport, Education and Society, 23(3), 229–243. https://doi.org/10.1080/13573322.2016.1174845

Sharma, V., Feldman, M., & Sharma, R. (2024). Telehealth Technologies in Diabetes Self-management and Education. Journal of Diabetes Science and Technology, 18(1), 148–158. https://doi.org/10.1177/19322968221093078

Turner, E. H. G., Lang, M. D. H., & Spiker, A. M. (2021). A narrative review of the last decade's literature on the diagnostic accuracy of septic arthritis of the native joint. Journal of Experimental Orthopaedics, 8(1), Article 3. https://doi.org/10.1186/s40634-020-00315-w

Turner, L., Hashimoto, D. A., Vasisht, S., & Schaye, V. (2024). Demystifying AI: Current State and Future Role in Medical Education Assessment. Hepatology, 99(4), S42–S47. https://doi.org/10.1097/ACM.0000000000005598

Urbina, J. T., Vu, P. D., & Nguyen, M. V. (2025). Disability Ethics and Education in the Age of Artificial Intelligence: Identifying Ability Bias in ChatGPT and Gemini. Archives of Physical Medicine and Rehabilitation, 106(1), 14–19. https://doi.org/10.1016/j.apmr.2024.08.014

van der Schyff, E. L., Ridout, B., Dip, G., Amon, K. L., Forsyth, R., Cert, G., & Campbell, A. J. (2023). Providing Self-Led Mental Health Support Through an Artificial Intelligence–Powered Chat Bot (Leora) to Meet the Demand of Mental Health Care. Journal of Medical Internet Research, 25, Article e46448. https://doi.org/10.2196/46448

Van Eetvelde, H., Mendonça, L. D., Ley, C., Seil, R., & Tischer, T. (2021). Machine learning methods in sport injury prediction and prevention: a systematic review. Journal of Experimental Orthopaedics, 8(1), Article 27. https://doi.org/10.1186/s40634-021-00346-x

Vergeer, I., Bennie, J. A., Charity, M. J., Harvey, J. T., van Uffelen, J. G. Z., Biddle, S. J. H., & Eime, R. M. (2017). Participation trends in holistic movement practices: A 10-year comparison of yoga/Pilates and t'ai chi/qigong use among a national sample of 195,926 Australians. BMC Complementary and Alternative Medicine, 17(1), Article 296. https://doi.org/10.1186/s12906-017-1800-6

Waśkiewicz, Z., Słomka, K. J., Grzywacz, T., & Juras, G. (2025). Ethical Bias in AI-Driven Injury Prediction in Sport: A Narrative Review of Athlete Health Data, Autonomy and Governance. AI (Switzerland), 6(11), Article 283. https://doi.org/10.3390/ai6110283

Wellmann, N., Marc, M. S., Stoicescu, E. R., Pescaru, C. C., Trusculescu, A. A., Martis, F. G., Ciortea, I., Crisan, A. F., Balica, M. A., Velescu, D. R., & Fira-Mladinescu, O. (2024). Enhancing Adult Asthma Management: A Review on the Utility of Remote Home Spirometry and Mobile Applications. Journal of Personalized Medicine, 14(8), Article 852. https://doi.org/10.3390/jpm14080852

Wu, C. H. (2022). Artificial-intelligence robot umpires in sailing race. Frontiers in Psychology, 13, Article 979657. https://doi.org/10.3389/fpsyg.2022.979657

Wurman, P. R., Barrett, S., Kawamoto, K., MacGlashan, J., Subramanian, K., Walsh, T. J., Capobianco, R., Devlic, A., Eckert, F., Fuchs, F., Gilpin, L., Khandelwal, P., Kompella, V., Lin, H. C., MacAlpine, P., Oller, D., Seno, T., Sherstan, C., Thomure, M. D., ... Kitano, H. (2022). Outracing champion Gran Turismo drivers with deep reinforcement learning. Nature, 602(7896), 223–228. https://doi.org/10.1038/s41586-021-04357-7