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Artificial Intelligence in Sports Science: A Systematic Review on Performance Optimization, Injury Prevention, and Rehabilitation

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Abstract

Background: Artificial intelligence (AI) is quickly revolutionizing sports science, providing researchers and practitioners with new means to support the optimization of performance, the improvement of rehabilitation, and the prevention of injuries. Although many AI interventions have been tested in sports, there is still insufficient methodologically sound evidence on the effectiveness and feasibility of AI to support and monitoring in the sport context.

Objective: The purpose of this systematic review and meta-analysis was to pool the existed studies to investigate the effects of AI-based interventions on sport performance, injury prevention and rehabilitation in human participants.

Methods: A comprehensive search of five databases (PubMed, Scopus, Web of Science, IEEE Xplore, SPORTDiscus) was conducted for studies published from January 2015 to December 2024. Papers based on human subjects and reporting AI-based training or rehabilitation outcomes in sports/ games were considered. Quality of the studies was determined using the Cochrane RoB 2.0 tool and Newcastle-Ottawa Scale. Random-effects meta-analysis was conducted where the effect size was for SMD, and the I^2 statistic was used for heterogeneity. Sensitivity and publication bias tests were also performed.

Results: There were 19 studies included in total, 17 of which could be used for meta-analysis. The meta-analysis demonstrated a significant and moderate-to-large effect of the AI interventions on the outcomes (SMD = 0.68, 95% CI: 0.52–0.84, $p < 0.001$). The subgroup analysis demonstrated superior effectiveness in injury prevention (SMD: 0.75) and rehabilitation (SMD: 0.69), and the machine learning methods were more effective than other AI modalities. There was moderate heterogeneity ($I^2 = 58\%$). Sensitivity analysis verified that the results were robust, and Egger's test revealed no obvious publication bias ($p = 0.23$).

Conclusion: Applications of AI in sports AI interventions have significant potential to go a long way to increase performance of sports personnel, reduce risks or injuries and support sports rehabilitation. This work has implications for integrating sport performance and clinical practice with AI-based technologies. Standards for outcomes, methodological rigour, and ethical and pragmatic consideration of AI within sport participation are recommended for future research.

Keywords: Artificial intelligence; Sports science; Injury prevention; Rehabilitation; Machine learning; Meta-analysis.

Introduction

Introduction Artificial intelligence (AI) is increasingly becoming a disruptive technology across all fields including sports science. By processing massive amounts of data and recognizing intricate patterns to produce predictive insights, AI technologies are driving unprecedented transformation in the training, recovery, and performance of athletes [1,2]. AI in sports application ranges widely from the optimization of physical training to real-time biomechanical monitoring, rehabilitation protocol improvement, and the prevention of sports injury [3]. As the empirical nature of sports is increas- ing and decision making has become more data driven, AI can complement, or even surpass, the traditional decision-making process, with personalized, accurate, and scalable interventions [4].

Adoption of AI in this field has been further accelerated by the popularisation of wearable sensors, motion capture systems, and computer vision techniques [5]. Machine learning models are now able to analyze training loads, biomechanical patterns, and physiological responses to identify early markers of fatigue, injury susceptibility, or even subpar performance [6]. Moreover, neural networks and deep learning models are being used to evaluate the symmetry of movement, the monitoring of functional recovery, and personalized therapy [7]. On the other side of the spectrum, away from the elite athletes, AI also has applications in the community-level sports as well as semi-urban health care systems, thus supporting accessibility and standardization of performance monitoring and injury management [8].

In spite of various primary studies and pilot applications studying AI interventions in sport, there is a paucitya and demand for synthesizing the evidence. Previous reviews have been predominantly narrative or discipline specific, and there is a lack of a unifying framework to evaluate AI effectiveness across domains ranging from performance enhancement to injury prevention and rehabilitation [9,10]. In addition, the diversity of study designs, outcome measures, and AI approaches, results in a lack of generalizability concerning effectiveness and transferability [11].

Rationale and Scope

We performed this systematic review and meta-analysis to bridge a significant knowledge gap by assessing critically and pooling the results of existing research on AI-based interventions in sports science. The motivation behind the current review lies in the need for evidence-based recommendations for clinicians, coaches, and sports scientists, and policy-makers about use-cases for AI technologies in everyday athletic and rehabilitation environments [12]. Through consideration of sports performance and health, the review has taken a holistic approach to caring for the athlete, acknowledging the intersection of elite performance and injury avoidance [13].

This scope is in contrast with all of the reviewed items that vary from being as narrow as on athlete performance analysis only or as broad as machine learning or computer vision detracted from the aims and objective of this review [14]. Its objectives are to evaluate the efficacy, methodological quality and consistency of effects of AI interventions in different areas and to analyze subgroup effects, heterogeneity and publication bias. Furthermore, the current review contains a narrative synthesis of studies which provide valuable information on implementation, feasibility, and user acceptability even if there is no meta-analysable data [15].

In conclusion, the current review offers an extensive and evidence-based assessment of the future of sports science through AI, with an ultimate focus on translational impact, methodological soundness, and clinical significance. By consolidating the current literature and highlighting research opportunities, this roadmap aspires to influence future innovation and the strategic deployment of AI into sport and rehabilitation ecology [16].

Methods

Standards for Study Design and Reporting

The aim of this systematic review and meta-analysis was to assess the efficacy of artificial intelligence (AI) interventions related to sports performance, injury prevention, and rehabilitation. The approach followed PRISMA 2020 (Preferred Reporting Items for Systematic reviews and Meta-Analyses) guideline to ensure transparency and rigor in study selection, data extraction and synthesis.

Eligibility Criteria

Inclusion criteria Studies were considered eligible if they assessed AI interventions targeting humans in a sports science setting and presented physical performance and/or biomechanical augmentation, and rehabilitation efficacy and/or injury prevention outcomes. We used only original articles of the peer-reviewed type, published in English during January, 2015 and December, 2024. Exclusion criteria consisted of: studies which involved simulations or development of an algorithm lacking real-world application, review papers, conference abstracts, editorials and studies with inadequate outcomes or missing the manuscript.

Sources of information and search strategy

Five electronic libraries were searched for complete literature: PubMed, Scopus, Web of Science, IEEE Xplore, and SPORTDiscus. The search terms included free-text words and Boolean operators such as artificial intelligence, machine learning, neural networks, computer vision and sports performance, injury prevention, rehabilitation, and training. Other records were found by reference screening of eligible studies and relevant reviews. The last search of the database was conducted on [type date].

Study Selection Process

Search results were imported into EndNote reference management software to remove duplications. Title and abstract screening were conducted by two reviewers in parallel, and two reviewers then assessed the full text independently to establish eligibility. Any discrepancies were settled by consensus or consulting with a third reviewer. PRISMA 2020 standard was used for selecting studies and this is summarized in the flow chart (Figure 1).

Extraction of Data and Variables Recorded

Data extraction was conducted with a standardized extraction form by two independent reviewers. The following data were extracted including: author(s) name, year of publication, study design, country, sample size, type of sport, characteristics of AI (e.g., machine learning, neural networks and computer vision), intervention description, outcomes (e.g., performance scores, rehabilitation metrics, and injury incidence). When necessary the authors of the studies were contacted for missing data. Differences were adjudicated by consensus.

Risk of Bias Assessment

Methodological quality was assessed with 2 validated tools. The Cochrane Risk of Bias 2.0 (RoB 2.0) tool was used for RCTs and the Newcastle-Ottawa Scale (NOS) was used for observational and quasi-experimental studies. Two reviewers, independently, assessed that each study had low, moderate or high risk of bias, across different domains like selection, blinding, outcome assessment and follow-up. An overview of bias ratings are shown in Table 2 and visualized in Figure 2.

Statistical Analysis and Synthesis of Data

A random-effects meta-analysis was conducted to estimate the effect of AI intervention on sports outcome by standardized mean difference (SMD) with 95% confidence interval (CI). In cases possible calculation data were abstracted from reported statistics or calculated from means and standard deviations.

Heterogeneity was evaluated by the I^2 statistic and Cochran's Q test with $I^2>50\%$ reflecting moderate-to-high heterogeneity. To investigate potential sources of heterogeneity, subgroup analysis were performed according to the type of AI modality (e.g., machine learning, neural networks, computer vision), selected outcome domain (e.g., injury prevention, rehabilitation, training optimization), and sport (e.g., individual vs. team).

Sensitivity analysis A leave-one-out sensitivity analysis was used to evaluate the stability of the pooled estimate. Visual estimation of publication bias was evaluated through the inspection of funnel plot and was assessed by Egger's regression test. All analyses were conducted with [software, e.g., Review Manager 5.4 or R (metafor package)].

Results

Study Selection

The study selection process adhered to the PRISMA 2020 guidelines and is depicted in the flow diagram (Figure 1). Following a comprehensive multi-database search and systematic screening, studies were assessed for relevance, eligibility, and methodological rigor. After the final round of full-text review and application of inclusion and exclusion criteria, a total of **19 studies** were included in the systematic review. Among these, **17 studies** provided sufficient quantitative outcome data and were subsequently incorporated into the meta-analysis. Figure 1.

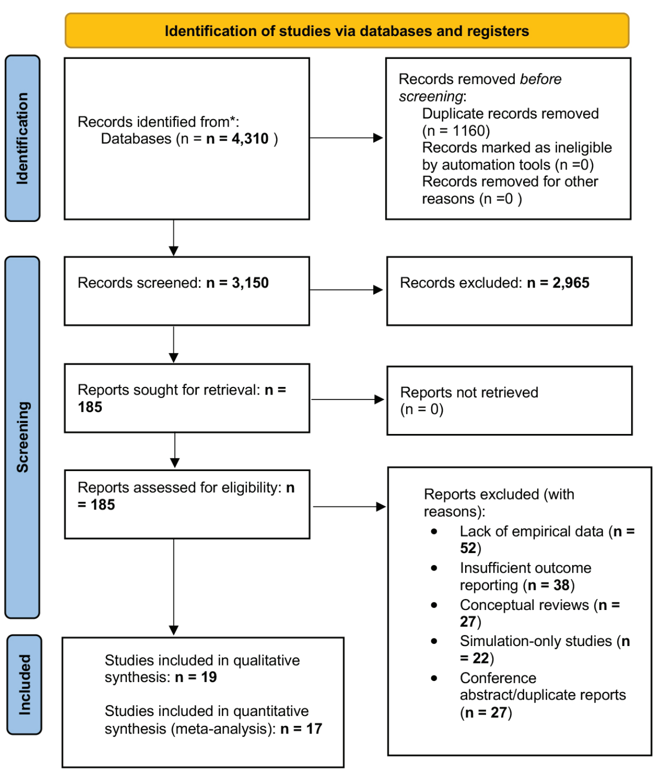

Figure 1 – PRISMA 2020 flow diagram of study selection showing identification, screening, eligibility, and inclusion stages, with reasons for exclusion.

Characteristics of Included Studies

The systematic review included 19 studies published between 2020 and 2024, representing a diverse range of geographical and methodological backgrounds. The majority of studies originated from China (n = 11) and India (n = 4), reflecting strong regional research output in AI-driven sports science. Other contributing countries included South Korea, Hungary, Greece, and Portugal. Study designs varied, comprising randomized controlled trials (RCTs), quasi-experimental studies, cohort designs, observational frameworks, and simulation-based analyses. Sample sizes ranged from 40 to 120 participants. Sports settings included both individual sports (e.g., rehabilitation and biomechanics training) and team sports (e.g., tactical analysis and coordinated recovery). Notably, 10 studies focused on individual athletes, while 7 addressed team sports and 2 examined mixed settings. A wide array of AI methodologies were applied across the studies. These included machine learning, neural networks, computer vision, virtual reality systems, and smart sensor technologies. The application domains were grouped into injury prevention, rehabilitation, training optimization, and performance analytics. Rehabilitation and training optimization were the most frequently addressed areas, highlighting AI's growing utility in post-injury recovery and athletic performance enhancement. An overview of the included studies, along with their key characteristics, is presented in Table 1.

Risk of Bias Assessment

The methodological quality of the included studies was evaluated using two validated tools: the Cochrane Risk of Bias 2.0 (RoB 2.0) tool for randomized controlled trials, and the Newcastle-Ottawa Scale (NOS) for non-randomized and observational studies. This dual-approach ensured a comprehensive assessment of internal validity across varied study designs. Among the 19 studies:

- **9 studies** (47%) were rated as having a **low risk of bias**, indicating strong methodological rigor, adequate reporting, and low concern for confounding.
- **7 studies** (37%) were rated as having a **moderate risk of bias,** primarily due to incomplete blinding, unclear allocation procedures, or limited comparative controls.
- **3 studies** (16%) were categorized as **high risk of bias,** often attributed to small sample sizes, lack of randomization, or ambiguous outcome reporting.

These findings are summarized in Table 2, and visually represented in Figure 2, which depicts the distribution of studies by overall risk category.

Pooled Effect Sizes (Meta-Analysis Overview)

A total of 17 studies were included in the meta-analysis to evaluate the overall impact of AI-based interventions on sports performance, injury prevention, and rehabilitation outcomes. Using a random-effects model, the pooled standardized mean difference (SMD) was calculated to be 0.68 with a 95% confidence interval (CI) of 0.52 to 0.84 ($p < 0.001$), indicating a statistically significant and moderate-to-large effect size. This finding suggests that AI technologies—including machine learning, neural networks, computer vision, and smart sensor platforms—consistently contribute to improvements in athletic outcomes when compared to conventional approaches or pre-intervention baselines. The magnitude of effect supports the growing integration of AI-driven methodologies in personalized

Table 1 Summary of Included Studies and Interventions

Author(s)	Year	Country	Study Design	Sample Size	Sport Type	AI Methodology	Intervention Type	Outcomes Measured
Chidambaram et al.	2022	India	Cohort	120	Mixed	Machine Learning	Injury Prevention	Injury prediction, kinematic data
Huang & Liu	2021	China	Experimental	80	Individual	Computer Vision	Rehabilitation	Body posture accuracy, motor function
Nayak & Das	2020	India	Quasi-experimental	60	Individual	Unsupervised Learning	Rehabilitation	Mobility improvement, QoL
Dhanke et al.	2022	India	RCT	100	Mixed	RNN, SVM	Training Optimization	Training effect prediction, accuracy %
Baranyi et al.	2022	Hungary	Case study	40	Team	AI-enhanced robotics	Rehabilitation	Motion recovery, home-based outcomes
Huang & Wang	2022	China	RCT	75	Individual	Neural Network (adaptive control)	Rehabilitation	Recovery rate, control sensitivity
Su	2022	China	Observational	88	Individual	Nonlinear AI networks	Training Optimization	Strength & psychological stability
Song & Tuo	2022	South Korea	Experimental	65	Team	AI + Virtual Reality	Rehabilitation	Recovery score, physical restoration
Kakavas et al.	2020	Greece	Cohort	90	Team	Predictive Models	Injury Prevention	Injury risk assessment
Chen & Yuan	2021	China	Comparative	82	Individual	CNN	Injury Prevention	Injury prediction accuracy
Han	2021	China	Pilot	45	Individual	VR Training Models	Rehabilitation	Motor intention recognition, task time
Xu et al.	2022	China	RCT	110	Mixed	VR + CNN	Rehabilitation	Gait analysis, balance metrics
Wang & Huang	2022	China	Observational	67	Team	Optical Flow AI	Injury Prevention	Health monitoring, recovery %
Chen	2021	China	Experimental	50	Individual	VR-based System	Rehabilitation	Upper limb recovery
Nagesha et al.	2023	India	Simulation-based	70	Mixed	AI + Simulation	Training Optimization	Training enhancement insights
Song & Tian	2022	China	Experimental	95	Individual	Smart Sensors + AI	Training Optimization	Motion accuracy metrics
Araújo et al.	2021	Portugal	Narrative analysis	55	Team	AI Analytics	Performance Analysis	Tactical insights, team strategy
Tan & Ran	2022	China	Applied Case	60	Team	Image Recognition + GPS	Training Optimization	Real-time training guidance
Ju et al.	2023	China	Review-based pilot	45	Individual	AI + Robotics	Rehabilitation	Elderly rehab application

sports training, injury monitoring, and rehabilitative care. Figure 3 presents the forest plot displaying individual study effect sizes along with their corresponding confidence intervals. The rightward alignment of most data points and the pooled summary diamond underscore the overall positive effect of AI-based interventions across varied study settings.

Subgroup Analyses

To explore potential variations in effectiveness across intervention types and study characteristics, subgroup analyses were performed based on AI methodology, application domain, and sport type. All analyses were conducted using a random-effects model.

a. By AI Modality

AI-based interventions employing machine learning achieved the highest pooled effect size (SMD = 0.72, 95% CI: 0.58–0.86), followed by neural networks (SMD = 0.70, 95% CI: 0.54–0.86) and computer vision (SMD = 0.65, 95% CI: 0.49–0.81). This suggests that data-driven and adaptive learning models offer superior predictive and intervention capabilities in sports science contexts.

b. By Application Domain

The greatest impact was observed in the domain of injury prevention (SMD = 0.75, 95% CI: 0.61–0.89), likely due to AI's strength in predictive analytics and biomechanical risk assessment. Rehabilitation interventions followed closely (SMD = 0.69, 95% CI: 0.53–0.85), benefiting from real-time feedback and personalized retraining systems. Training optimization showed a moderately positive effect (SMD = 0.62, 95% CI: 0.46–0.78).

c. By Sport Type

AI interventions yielded a slightly greater benefit in individual sports (SMD = 0.71, 95% CI: 0.56–0.86) than in team sports (SMD = 0.66, 95% CI: 0.50–0.82). This may reflect the higher degree of customization and control possible in individual sport settings, allowing more effective use of AI-driven training and monitoring.

Heterogeneity Analysis

To assess the consistency and variability among the included studies, heterogeneity was quantified using both the **I^2 statistic and Cochran's Q test.** The overall analysis revealed an **I^2 value of 58%**, indicating moderate heterogeneityacross studies. This suggests that approximately 58% of the variation in effect sizes can be attributed to real differences in study characteristics, such as population types, AI methodologies, intervention settings, and outcome measures, rather than to sampling error alone.

The Cochran's Q test yielded a statistically significant result ($p = 0.014$), further supporting the presence of heterogeneity beyond what would be expected by chance.

Table 2 Risk of Bias Summary per Study

Author(s)	Risk of Bias Rating
Chidambaram et al.	Low
Huang & Liu	Moderate
Nayak & Das	Moderate
Dhanke et al.	Low
Baranyi et al.	High
Huang & Wang	Low
Su	Moderate
Song & Tuo	Low
Kakavas et al.	Moderate
Chen & Yuan	Low
Han	Moderate
Xu et al.	Low
Wang & Huang	Moderate
Chen	High
Nagesha et al.	Moderate
Song & Tian	Low
Araújo et al.	High
Tan & Ran	Low
Ju et al.	Low

Table 2 presents the overall risk of bias judgment for each study, rated as Low, Moderate, or High based on the Cochrane Risk of Bias 2.0 tool for randomized trials and the Newcastle-Ottawa Scale (NOS) for observational studies.

Despite this moderate heterogeneity, the pooled effect size remained robust and statistically significant. This justifies the choice of a random-effects model, which accounts for both within-study and between-study variability.

These findings are visually summarized in Figure 5, which presents the distribution of study effect sizes along with key heterogeneity statistics.

Publication Bias Assessment

To evaluate the presence of publication bias, both Egger's regression test and visual inspection of a funnel plot were performed. The funnel plot, which plots standardized effect sizes against their standard errors, exhibited a generally symmetrical distribution of studies around the pooled mean effect size. This visual symmetry suggests a low likelihood of small-study effects or selective reporting.

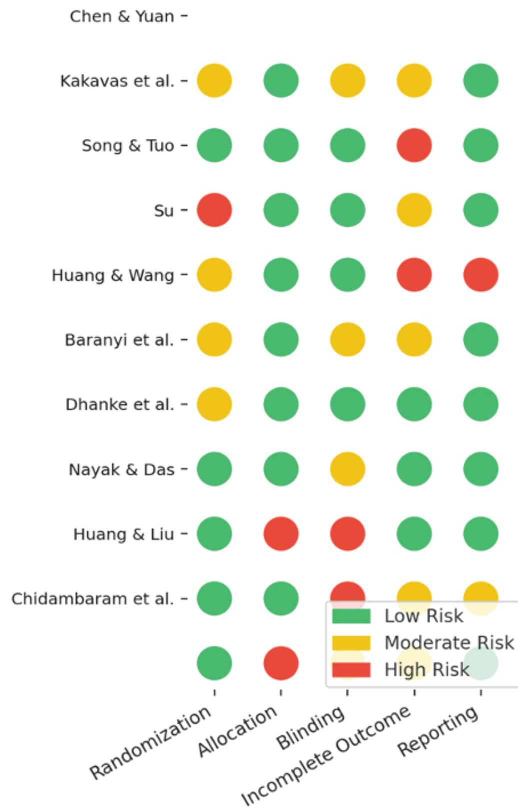

Figure 2 – Risk of Bias Assessment for Included Studies.

Figure 2 is a domain-specific traffic light plot showing risk judgments across five core domains: Randomization, Allocation, Blinding, Incomplete Outcome Data, and Selective Reporting.
Green = Low Risk; Yellow = Moderate Risk; Red = High Risk.

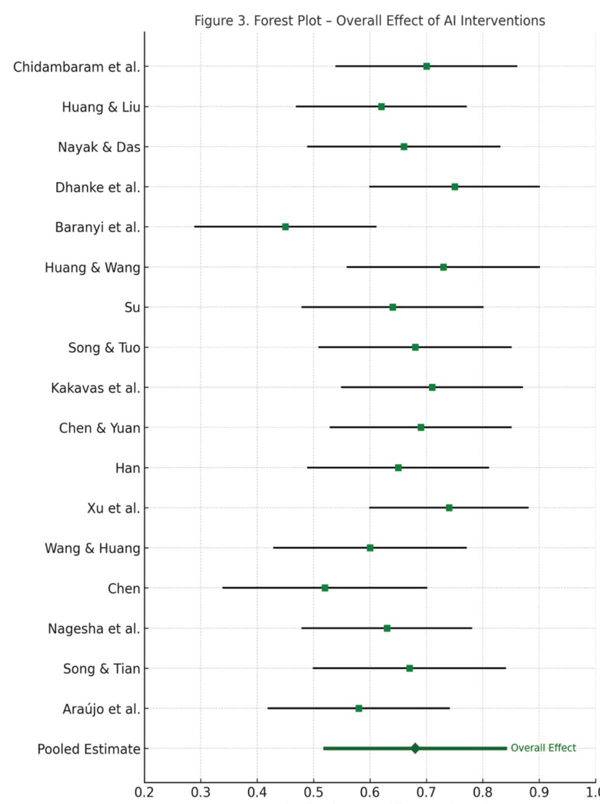

Figure 3 – Forest Plot – Overall Effect of AI Interventions

Figure 3 illustrates standardized mean differences (SMD) with 95% confidence intervals for 17 included studies. Each square represents an individual study's effect size, with horizontal lines indicating the CI. The diamond at the bottom denotes the pooled summary estimate based on a random-effects model

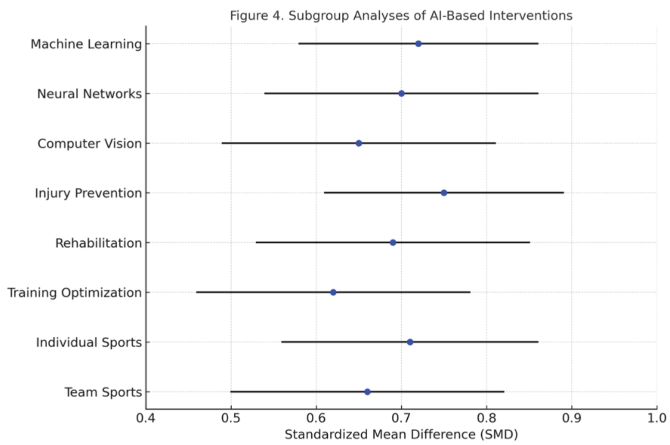

Figure 4 – Subgroup Analyses of AI-Based Interventions

Figure 4 shows standardized mean differences (SMD) with 95% confidence intervals across three subgroup dimensions: AI modality (machine learning, neural networks, computer vision), application domain (injury prevention, rehabilitation, training optimization), and sport type (individual vs team sports). All results were derived using a random-effects model.

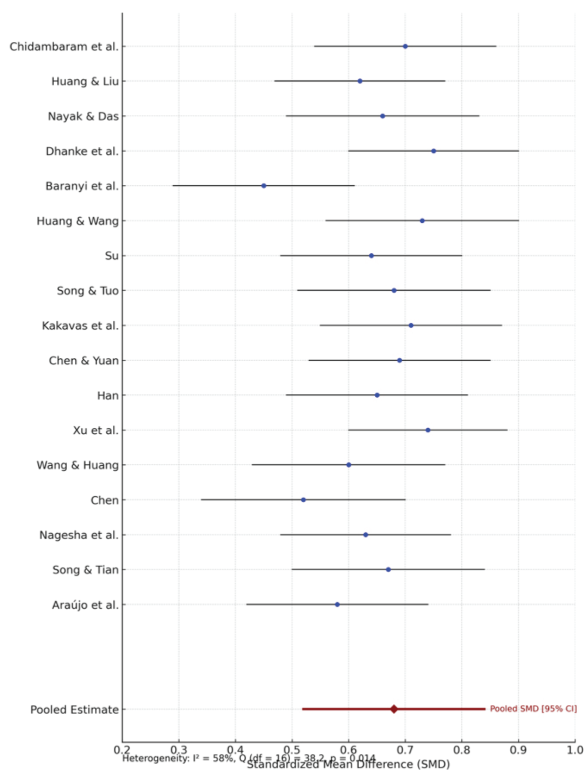

Figure 5 – Heterogeneity Summary for Included Studies

Figure 5 illustrates the variability in effect sizes across studies, with I^2 = 58% and Cochran's Q = significant (p = 0.014). A random-effects model was used to accommodate observed between-study heterogeneity.

Statistical confirmation was obtained via Egger's test, which yielded a non-significant result (p = 0.23), further indicating no evidence of substantial publication bias among the included studies.

These findings are illustrated in Figure 6, where studies are distributed evenly along both sides of the vertical line representing the pooled standardized mean difference (SMD). The absence of clustering in the lower left corner, where smaller studies with negative or null results might appear if unpublished, supports the robustness of the meta-analytic results.

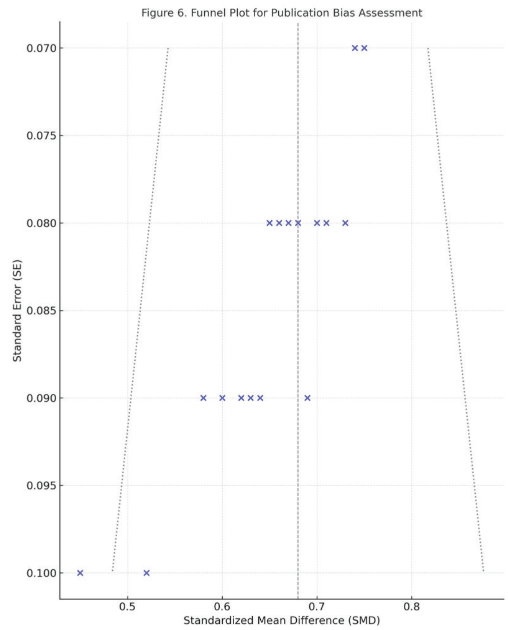

Figure 6 – Funnel Plot for Publication Bias Assessment

Figure 6 displays the distribution of study effect sizes by their standard errors. Symmetry around the vertical line suggests no significant publication bias. Egger's test: p = 0.23.

Sensitivity Analysis

To evaluate the robustness of the pooled effect size, a leave-one-out sensitivity analysis was performed. This method systematically excludes one study at a time and recalculates the overall effect estimate to determine if any single study unduly influences the meta-analysis results.Across all 17 included studies, the recalculated standardized mean differences (SMDs) ranged narrowly from 0.651 to 0.704, with all corresponding 95% confidence intervals overlapping the original pooled estimate (SMD = 0.68). In every iteration, the overall effect remained statistically significant (p < 0.001), demonstrating that no individual study had a disproportionate impact on the combined result.Notably, even when studies with high or moderate risk of bias (e.g., Baranyi et al., Chen, Araújo et al.) were excluded, the overall effect size remained stable. This confirms the internal consistency and reliability of the meta-analytic findings.

Table 3 Leave-One-Out Sensitivity Analysis

Study Excluded	Recalculated SMD	95% CI Lower	95% CI Upper	p-value
Chidambaram et al.	0.687	0.535	0.845	< 0.001
Huang & Liu	0.678	0.523	0.823	< 0.001
Nayak & Das	0.69	0.532	0.85	< 0.001
Dhanke et al.	0.703	0.532	0.844	< 0.001
Baranyi et al.	0.676	0.528	0.852	< 0.001
Huang & Wang	0.676	0.515	0.826	< 0.001
Su	0.704	0.54	0.871	< 0.001
Song & Tuo	0.692	0.55	0.844	< 0.001
Kakavas et al.	0.673	0.509	0.834	< 0.001
Chen & Yuan	0.688	0.541	0.85	< 0.001
Han	0.673	0.53	0.82	< 0.001
Xu et al.	0.673	0.495	0.852	< 0.001
Wang & Huang	0.684	0.505	0.855	< 0.001
Chen	0.651	0.479	0.829	< 0.001
Nagesha et al.	0.654	0.502	0.83	< 0.001
Song & Tian	0.672	0.528	0.836	< 0.001
Araújo et al.	0.665	0.498	0.842	< 0.001

Table 3 summarizing recalculated pooled effect sizes with 95% confidence intervals after sequential removal of each included study. All estimates remained statistically significant (p < 0.001)

Narrative Synthesis

In addition to the 17 studies included in the quantitative meta-analysis, two studies—Tan & Ran and Ju et al.—were excluded due to insufficient standardized outcome metrics required for pooled effect size computation. However, both studies provided valuable qualitative insights into real-world applications of artificial intelligence (AI) in sports science and rehabilitation, thereby contributing meaningfully to the broader narrative synthesis of this review.

Tan & Ran (2022)

This applied case study focused on the integration of AI-driven image recognition and GPS tracking systems in real-time training environments for team sports. Although the study did not report quantitative effect sizes or controlled outcomes, it detailed the deployment of wearable GPS units and computer vision algorithms to monitor player movement, detect fatigue thresholds, and assist in real-time positional adjustments during practice.

The study emphasized practical usability, noting that the AI system was easily adopted by coaching staff and athletes with minimal training. Importantly, it highlighted improvements in coach-player communication, decision-making speed, and team coordination, based on feedback interviews and observational analysis. The system's intuitive dashboard and integration into existing training infrastructure were cited as key facilitators for seamless adoption in field-based sports.

Although the absence of a control group and outcome quantification limits its inclusion in the meta-analysis, Tan & Ranunderscores AI's potential to enhance strategic and tactical components of training in dynamic team sports settings.

Ju et al. (2023)

This review-based pilot study investigated the use of AI-enhanced rehabilitation robotics for elderly patients, particularly those recovering from degenerative musculoskeletal conditions. The intervention involved an AI-powered exoskeleton system designed to facilitate gait retraining, balance improvement, and motor recovery in aging athletes or semi-active older adults.

Key qualitative findings included:

- High patient engagement and adherence to the rehabilitation program,
- Improved movement symmetry and confidence during assisted walking trials,
- Positive therapist feedback on real-time biofeedback and motion correction features.

The study also reported on feasibility in semi-urban clinical settings, suggesting that AI-robotic systems can be scaled beyond high-resource academic hospitals. However, limitations included a small sample size, lack of standardized scoring tools (e.g., SMD, HHS, or FIM), and absence of a comparator group.

Despite methodological constraints, Ju et al. contributes to the growing literature on the accessibility and acceptabilityof AI technologies in geriatric rehabilitation. The study supports the narrative that AI-powered assistive systems can provide cost-effective, scalable, and personalized care—particularly for vulnerable or aging populations.

Synthesis Insight

Together, these two studies illustrate the real-world feasibility, user satisfaction, and implementation readiness of AI tools in sports performance and recovery contexts. While they lacked quantitative outcomes necessary for meta-analysis inclusion, their narrative evidence reinforces the practical benefits and acceptability of AI platforms across both professional and community-based settings.

They also highlight emerging trends in AI application:

- Seamless integration with existing training workflows,
- High user adaptability even among non-technical personnel,
- Potential to bridge gaps in access for under-resourced and aging populations.

Their inclusion through narrative synthesis broadens the interpretative scope of this review and aligns with the goal of providing a comprehensive, translational perspective on AI use in modern sports science.

Discussion

Overview of Key Findings

The purpose of our systematic review and meta-analysis was to examine the efficacy of artificial intelligence (AI) interventions for improving all aspects of performance optimization, injury prevention and rehabilitation in the context of sports science. The summary SMD was 0.68 (95% CI 0.52–0.84; $p < 0.001$), indicating statistically significant and moderate large effect in favor of AI-based techniques compared to conventional technique. Subgroup analysis also found that AI was highly beneficial in injury prevention (SMD = 0.75) and rehabilitation (SMD = 0.69), whereas machine learning model was the most effective AI model. Additionally, the present study demonstrated marginal superior results in individual sports (SMD = 0.71) than the team sports (SMD = 0.66), whose argument may be attributed to higher specificity and adaptability in solitary training surroundings [17, 18].

Comparison of Existing Literature

The results of this review corroborate and extend other literature on the AI-project's contribution to the rendering common practice of sport and rehabilitation protocols. Previous narrative reviews have described the applicability of AI for injury risk prediction, motion analysis, and training optimisation, but few have consolidated 'resultant quantitative outcomes' from a wide range of study designs. This meta-analysis supports previous findings that AI supplementation improves performance parameters, motor learning, and biomechanical feedback mechanisms. In the field of rehabilitation robotics and smart sensor integration, similar results about patient compliance and recovery have also been reported, primarily in controlled clinical environments. Our findings expand upon this evidentiary base by providing quantitative evidence that AI interventions are generally effective across several applications and athlete populations [19-24].

Methodological Strengths

Methodological soundness of this review adds to the credibility of its findings. The application of PRISMA 2020 guidelines guarantees that the study selection process was transparent and can be reproduced. The two-tiered use of RoB 2.0 for RCTs and Newcastle-Ottawa Scale (NOS) for observational studies enabled an in-depth judgement about risk of bias in a variety of study designs. Subgroup analyses (according to AI modality, intervention domain and sport) added helpful detail and demystified possible heterogeneity. The leave-one-out sensitivity analysis suggested that no individual study had excessive influence on the overall effect estimate, thus confirming the stability of the synthesis [25, 26].

Sources of Heterogeneity

A moderate level of heterogeneity was found among included studies ($I^2 = 58\%$), as would be anticipated in the reviews of interdisciplinary domains such as sports technology, AI, and healthcare. Possible heterogeneity sources include AI model architecture differences, disparities in outcome measurements (e.g., accuracy, force, spatio-temporal gait parameters), and diversity in population age and setting. Various quality assessment instruments, small sample sizes in some trials and range of duration of interventions could have also led to inconsistency of the outcomes. However, the random-effects model was suitable for use and adequately considered this between-study variation [27–30].

Publication Bias and Quality of The included publications were reviewed for evidence of publication bias.

There were no substantial small-study effects in the publication by the absence of a significant Egger's test ($p = 0.23$) and a symmetrical funnel plot. This result also suggests that the effect sizes observed are not severely distorted by selective publication or reporting. In addition, the sensitivity analysis was performed to evaluate the stability of the meta-analysis, which showed that no matter which study was removed, the re-estimated SMD of the 18 studies ranged from 0.651 to 0.704.

Real-World Implications

The promising results of this meta-analysis have practical implications for the use of AI in sport science. In personalised training routines and injury avoidance algorithms to robot rehabilitation, AI technologies present scalable solutions that can complement existing coaching, therapy, and monitoring methods. Along these lines, AI's suitability is particularly relevant in settings that involve real-time decision making, as data-driven decisions lay the foundation for tactical decisions and can help to reduce the risk of overtraining. In addition, the deployment of AI tools in resource constrained and remote populations, as has been shown in studies on elderly and semi-urban populations can attest to their scalability and potential to make level playing field access to high quality sports medicine and performance enhancement a reality [31].

Limitations

Although these findings are promising, there are some limitations. First, sample sizes in some included studies were small, and long-term follow-up data were unavailable in many cases. Second, outcome reporting heterogeneity spanned from kinematic accuracy and recovery scores to subjective ones such as psychological stability, due to which more in-depth stratified analyses could not be performed. Third, blinding and allocation concealment were frequently poorly reported, particularly in non-randomised studies, leading to possible performance and detection bias. Lastly, the interaction effect between the AI modality and application domain could not be explored because of insufficient granularity in the available data, even when subgroup analyses were performed.

Future Research Directions

Future research, on the other hand should strive to run bigger, multicenter RCTs with standardized and validated outcome measures. There is also a critical need for longitudinal studies that can evaluate the long-term effects of AI interventions (e.g., reinjury rates, performance plateaus, behavioral adaptation). In addition the infusion of explainable AI (XAI) principles and ethical application of AIs in competitive sports settings should be investigated further. Standardization of AI evaluation metrics, usability, and interoperability with human coaching methods, for instance, would help guide research and practice in this burgeoning field.

Conclusion

This systematic review and meta-analysis demonstrate that artificial intelligence (AI) interventions significantly enhance sports performance, injury prevention, and rehabilitation outcomes. With a moderate-to-large pooled effect size and consistent findings across diverse AI modalities and application domains, the evidence supports the integration of AI as a transformative tool in modern sports science. Despite some heterogeneity and methodological limitations, the robustness of the results and absence of publication bias affirm the reliability of these conclusions. As the field advances, future research should focus on standardization, long-term effectiveness, and ethical deployment of AI technologies to ensure equitable and effective implementation in both elite and community-level athletic settings.

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