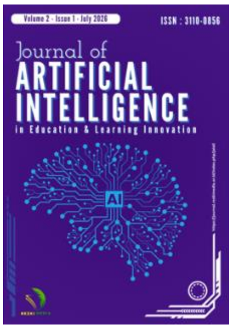

Artificial intelligence-supported motor skill performance in physical education and sport: A systematic review and meta-analysis informed by motor learning theory

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ABSTRACT

Background: Artificial Intelligence (AI) has increasingly been integrated into physical education (PE) to support motor learning through technologies such as computer vision, motion tracking, intelligent tutoring systems, virtual reality, and generative AI. However, evidence regarding its effectiveness remains fragmented across different intervention types and learning contexts.
Objectives: This study aimed to evaluate the effects of AI-supported interventions on motor skill performance in physical education and sport settings and to synthesize complementary learning-related outcomes.
Methods: A systematic review and meta-analysis were conducted in accordance with PRISMA 2020. Scopus, PubMed, and ProQuest were searched through 10 May 2026. Eligible studies evaluated AI-supported, adaptive, or intelligent interventions in physical education, sport, or motor skill-learning contexts and reported learner-level motor performance; complementary learning-related outcomes were synthesized narratively. Risk of bias was assessed using RoB 2 and ROBINS-I, and standardized mean differences (SMDs) with 95% confidence intervals (CIs) were synthesized using a random-effects model.
Results: Fifteen studies were included in the qualitative synthesis; six contributed to the meta-analysis and nine were synthesized narratively. The pooled estimate favored the designated AI-supported experimental conditions over their comparators (SMD = 3.15, 95% CI 1.86–4.44; $p < .001$; $I^2 = 98\%$). Given the small evidence base, very high heterogeneity, and variable risk of bias, the magnitude of this pooled effect is uncertain. Qualitative findings concerned short-term motor skill performance and complementary outcomes such as engagement, motivation, learning interest, and self-directed learning.
Conclusions: AI-supported interventions may improve short-term motor skill performance in some physical education and sport contexts and may support complementary learning-related outcomes. However, the evidence is preliminary and highly heterogeneous, and immediate post-intervention performance should not be interpreted as definitive evidence of durable motor learning, retention, or transfer. AI should be considered a complementary pedagogical tool rather than a replacement for teacher or coach expertise.

Keywords: artificial intelligence; motor skill performance, physical education, meta-analysis, students, skill acquisition.

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INTRODUCTION

Advances in Artificial Intelligence (AI) have brought significant changes to various fields of education, including physical education (PE) (Lee & Lee, 2021; Miller et al., 2024; Wang & Wang, 2024). Unlike cognitive learning, which focuses on acquiring knowledge, physical education emphasizes mastering motor skills through practice, feedback, movement correction, and continuous repetition. In practice, physical education teachers often face limitations in providing real-time, individualized feedback to all students, especially in classes with large student populations (Chen, 2025; Lee & Lee, 2021; Ma et al., 2025). This situation can hinder motor learning, as the quality and accuracy of feedback are key determinants of successful motor skill acquisition. With advances in AI technologies such as computer vision, machine learning, pose estimation, intelligent tutoring systems, and generative AI, various learning systems can now provide automated motion analysis, personalized feedback, and adaptive exercise recommendations (Ashwin et al., 2023; Reddy Basani et al., 2025; Zhao, 2025). Nevertheless, the effectiveness of AI in improving motor learning outcomes in physical education remains mixed and requires a more comprehensive synthesis of scientific evidence.

In recent years, research on AI in education has grown rapidly. Various studies show that AI can enhance the personalization of learning, the efficiency of feedback, learner engagement, and the quality of the learning process through adaptive learning systems (Halkiopoulos & Gkintoni, 2024; Sajja et al., 2024; Sari et al., 2024; Yekollu et al., 2024). However, most studies on AI in education still focus on cognitive domains, such as mathematics, language, or science. In contrast, research specifically evaluating the impact of AI on motor learning and movement skills in the context of physical education remains relatively limited. Therefore, a systematic review and meta-analysis are needed to synthesize the available empirical evidence, identify patterns of AI intervention effectiveness, and produce quantitative estimates of the magnitude of AI's association with short-term motor skill performance. This synthesis approach is essential for providing a stronger scientific foundation for policy development, instructional design, and the implementation of AI technology in physical education.

Several recent studies have begun to demonstrate the potential of AI in supporting motor learning. Pullen & Seffens (2018) developed a Kinect-based machine learning system to analyze yoga skills. They found that the system was capable of identifying movement patterns with a very high degree of accuracy and supporting the process of motor skill acquisition. Furthermore, Rauter et al. (2019) demonstrated that adaptive feedback on a robotic trainer can accelerate motor learning compared with conventional feedback approaches. In the context of online physical education, Ma et al. (2025) reported that an AI system based on pose recognition and real-time feedback significantly improved students' movement quality, execution fluency, and learning engagement. Another study by Hsia et al. (2025) showed that a gamified intelligent tutoring and feedback system based on Self-Determination Theory significantly improved yoga skill performance and learning engagement compared with a non-gamified AI-supported intelligent tutoring and feedback system. Additionally, Huang et al. (2026) reported that the combination of gamification and AI-based movement assessment increased learning engagement and improved the quality of students' movement performance.

Although these results indicate a positive trend, several important research gaps remain. Pullen & Seffens (2018) primarily validated a machine-learning-based motion recognition system and did not extensively evaluate its effectiveness in a physical education context. Rauter et al. (2019) demonstrated the benefits of adaptive feedback in a laboratory setting but did not describe its implementation in real-world physical education learning. Ma et al. (2025) demonstrated the effectiveness of real-time AI feedback in online learning, but only for a single motor skill type. Hsia et al. (2025) focused largely on motivation and engagement in yoga learning, whereas Huang et al. (2026) emphasized the integration of gamification and AI-based movement assessment. Overall, these studies suggest that AI can support motor learning through personalization and adaptive feedback. However, the evidence remains dispersed across intervention modalities, educational contexts, and outcome measures. Thus, this study provides a systematic review and meta-analysis that integrates different types of AI technologies and estimates their pooled association with short-term motor skill performance in physical education and sports.

The growing body of research on AI in physical education has generated valuable insights into the role of adaptive technologies in supporting motor learning. However, findings have largely been reported within isolated domains, such as computer vision-based feedback, virtual reality training, intelligent tutoring systems, or generative AI applications. Consequently, the broader pattern of evidence regarding the effectiveness of AI-supported motor learning remains unclear. This study addresses this issue by integrating evidence across multiple AI modalities and educational contexts, thereby offering a consolidated understanding of their collective association with motor skill performance and related learning outcomes. Such an approach enables a more robust interpretation of AI's pedagogical value beyond the outcomes of individual interventions. To the authors' knowledge, no previous review has quantitatively synthesized the effects of diverse AI-supported interventions on motor learning outcomes within physical education contexts.

Theoretically, this study is grounded in Motor Learning Theory, which holds that motor learning is a process of relatively permanent change in the ability to produce movements resulting from practice and experience (Magill & Anderson, 2010; Schmidt et al., 2018). Motor learning theory emphasizes the importance of practice, feedback, error correction, variability in practice, and continuous adaptation in acquiring motor skills (Magill & Anderson, 2010; Schmidt et al., 2018). The contemporary motor learning perspective also identifies augmented feedback and knowledge of performance as key factors in improving movement quality and accelerating skill formation (Dyer et al., 2015; Lauber & Keller, 2014). In this context, AI technology has the potential to reinforce the principles of motor learning by providing real-time feedback, automated motion analysis, personalized training, and continuous performance monitoring. Thus, AI-supported systems can function as forms of augmented feedback when they provide performance-contingent information, automated movement analysis, or adaptive practice support (Han, 2025; Stanney et al., 2022; Vandevoorde et al., 2022).

Based on this background, the objective of this study is to evaluate the effects of AI-supported interventions on motor skill performance in physical education and sport through a systematic review and meta-analysis. The review also synthesizes complementary learning-related outcomes, including motivation, engagement, self-efficacy, health literacy, and responses to AI-supported feedback. Retention and transfer are considered separately when reported because they provide stronger evidence of motor learning than immediate post-intervention performance. The findings are intended to inform educators, coaches, technology developers, and policymakers while preserving the central role of professional pedagogical judgment.

METHODS

Search Strategy

This study employed a systematic review and meta-analysis design, following the 2020 Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure transparency and consistency in reporting quantitative and qualitative evidence synthesis (Page et al., 2021). The research protocol was registered on the Open Science Framework (OSF) on May 10, 2026 (https://osf.io/kwgz7/overview; DOI: 10.17605/OSF.IO/KWGZ7). All supplementary materials—including the search strategies, data extraction sheets, risk-of-bias domain judgments, excluded studies list, and RevMan analysis files—are publicly available on OSF at https://doi.org/10.17605/OSF.IO/KWGZ7.

The literature search was conducted across three electronic databases (Scopus, PubMed, and ProQuest) using database-specific search strategies based on the PICOS framework. The search combined controlled vocabulary and free-text keywords related to artificial intelligence, motor learning, and physical education, connected using Boolean operators (AND, OR), field tags, and wildcards. The final search was conducted on May 10, 2026. Searches were restricted to English-language, peer-reviewed journal articles published between 2015 and 2026. The full, database-specific search strings, including all applied filters and limits for Scopus, PubMed, and ProQuest, are provided in Supplementary Table 1 page S1. A total of 108 records were identified across the databases: Scopus (n = 80), PubMed (n = 14), and ProQuest (n = 14). After duplicate removal using Rayyan and manual verification, 21 duplicate records were removed, leaving 87 records for title and abstract screening.

Study Selection and Eligibility Criteria

The study selection process consisted of several stages: screening titles and abstracts, full-text assessment, and final evaluation against inclusion and exclusion criteria. A total of 87 articles were screened based on their titles and abstracts. Of these, 47 articles were excluded because they did not align with the defined research outcomes, study design, population, or intervention type.

Subsequently, 40 reports were sought for retrieval. Three reports could not be retrieved, leaving 37 reports for full-text eligibility assessment. During the full-text assessment, 22 reports were excluded because they did not meet the predefined eligibility criteria, including wrong intervention, wrong study design, wrong outcome, or other PICOS-related reasons.

The inclusion criteria for this study are as follows:

1. The study addresses the use of AI in motor learning or physical education.
2. The study is conducted in the context of physical education, sports, or motor skill learning.
3. The study used an experimental, quasi-experimental, controlled intervention, or pre-post intervention design evaluating an AI, adaptive, or intelligent system; a non-AI comparator was not required for inclusion in the qualitative synthesis.

4. The study reported quantitative learner-level motor performance data; inclusion in the meta-analysis additionally required an interpretable between-group comparison and extractable group-level statistics (sample size, mean, and standard deviation or convertible equivalents).
5. The article is published in a peer-reviewed journal.
6. The article was published between 2015 and 2026.
7. The article is in English.
8. The full text is accessible.
9. Pilot, validation, or technical development studies were eligible for qualitative synthesis only when they reported learner-level motor performance outcomes rather than technical algorithm performance alone.

Exclusion criteria include:

1. Review articles, systematic reviews, meta-analyses, editorials, conference proceedings, theses, or book chapters.
2. Research unrelated to motor learning or physical education.
3. Studies focused solely on medical rehabilitation without a context of sports learning or education.
4. Digital technologies that do not utilize AI, adaptive, or intelligent systems, and studies reporting only technical algorithm performance without learner-level motor outcomes.
5. Studies that do not report motor learning outcomes.
6. Purely qualitative studies.
7. Duplicate articles.
8. Non-English articles.

Based on this selection process, 15 studies were included in the qualitative synthesis, of which six studies with complete extractable statistical data were included in the meta-analysis. All eligible studies were retained in the qualitative synthesis; however, only studies reporting sufficient group-level quantitative data, including sample size, mean, and standard deviation or convertible equivalent statistics, were eligible for quantitative synthesis. The remaining nine studies were synthesized narratively because compatible effect sizes could not be calculated from the reported data. A detailed classification of all 15 included studies and the rationale for their qualitative or quantitative synthesis eligibility are provided in Supplementary Table 2 page S3.

Study Characteristics

The study characteristics extracted included author, year of publication, country of research, study design, sample size, participant characteristics, type of AI intervention, comparator condition, duration of intervention, study outcomes, and primary study results. The study population consisted of school and college students, as well as sports learners engaged in motor learning and physical education activities. AI interventions identified in the studies included intelligent tutoring systems, computer vision, motion-tracking systems, virtual-reality-based learning, AI-supported feedback systems, and adaptive motor learning systems.

The primary quantitative outcome was defined as motor skill performance, encompassing immediate post-intervention measures of skill execution, movement accuracy, sport-specific performance, and motor proficiency. Retention and transfer were treated as distinct indicators of motor learning and were reported separately when available. Each included study was mapped to its outcome domain, and the exact variable selected for quantitative or qualitative synthesis is reported in Supplementary Table 3 page S4 page S4-S8.

Skill acquisition refers to improvement in execution of a target skill; movement accuracy refers to refinement of movement quality; sport-specific performance refers to successful task execution within a sporting context; and motor proficiency refers to broader movement competence. Retention refers to maintenance of performance after a period without practice, whereas transfer refers to application of learning to a novel task or context. General health-related fitness outcomes were not treated as motor learning outcomes unless they directly represented performance of the targeted motor task.

Because most included studies assessed outcomes immediately after the intervention, pooled effects were interpreted as effects on short-term motor skill performance rather than definitive evidence of relatively permanent motor learning. Retention and transfer were treated as distinct outcomes and synthesized separately when reported. Complementary outcomes—including motivation, engagement, self-efficacy, health literacy, learning interest, attitudes, and responses to AI-supported feedback—were synthesized narratively because measurement instruments and reporting were too heterogeneous for quantitative pooling. These psychological and behavioral outcomes were not treated as motor performance or as direct evidence of motor learning.

Risk of Bias Assessment

Methodological quality assessments were conducted to evaluate the risk of bias in the included studies. Randomized controlled trials (RCTs) were assessed using the Cochrane Risk of Bias Tool version 2 (RoB 2), while non-randomized studies were assessed using the Risk of Bias in Non-randomized Studies of Interventions (ROBINS-I) (Sterne et al., 2016; Sterne et al., 2019). Two reviewers independently assessed the risk of bias for all included studies. Any disagreements were resolved through discussion until a consensus was reached. Risk-of-bias visualizations were created using the RobVis application to generate traffic light plots and summary plots (McGuinness & Higgins, 2021). Detailed study-level and domain-level risk-of-bias judgments are provided in Supplementary Tables 5a and 5b page S9-S10.

Intervention and Comparator Classification

For eligibility, AI-supported interventions were defined as systems using machine learning, computer vision or pose estimation, intelligent or adaptive algorithms, or generative AI to analyze movement, generate or adapt feedback, or personalize practice. Digital technologies without an AI, adaptive, or intelligent component were excluded. Eligible comparator conditions included conventional or traditional instruction, non-AI controls, active digital or technology-supported comparators, and alternative AI-supported systems. Accordingly, some contrasts estimated the incremental value of an AI-supported enhancement rather than a simple AI-versus-non-AI effect; notably, the Hsia comparison contrasted the gamified G-ITIFS with a non-gamified C-ITIFS that was itself an intelligent tutoring and feedback system.

Study Results and Calculations of Effect Size

Six study-level comparisons were included in the quantitative synthesis. Post-intervention group means and corresponding standard deviations were used because these were the most consistently reported compatible statistics. For the quantitative comparisons, the selected outcome, assessment time point, sample size, and effect direction were recorded; the exact outcomes selected and their rationale are summarized in Supplementary Table 3 page S4. Because instruments differed across studies, effects were expressed as Hedges' g standardized mean differences (SMDs) and synthesized using a random-effects model. Positive values were coded to favor the designated experimental condition. Effect sizes were interpreted descriptively using conventional benchmarks of approximately 0.2 (small), 0.5 (moderate), and 0.8 (large), while recognizing that interpretation depends on the underlying measure and context.

Secondary Analysis

A narrative secondary synthesis was conducted for complementary learning-related outcomes that could not be statistically pooled because measurement instruments and indicators were heterogeneous. These outcomes included learning motivation, student engagement, self-efficacy, health literacy, and responses to feedback. Intervention characteristics—including virtual reality, gamified intelligent tutoring systems, adaptive feedback systems, generative AI, and AI-based motion tracking—were also summarized narratively.

Statistical Analysis

The meta-analysis was conducted using Review Manager (RevMan) version 5.4. A random-effects model was used because intervention types, learning contexts, participant characteristics, comparator conditions, and outcome measures varied across studies. Data were analyzed as SMDs with 95% CIs, and heterogeneity was evaluated using I^2 and the chi-square test. I^2 was interpreted in conjunction with clinical and methodological diversity; values in the 75–100% range were treated as indicating considerable heterogeneity. Results were visualized using a forest plot. Because only six studies were included in the quantitative synthesis, subgroup analysis, meta-regression, publication-bias assessment, and formal small-study-effect testing were not performed. A complete leave-one-out sensitivity analysis was conducted by iteratively removing each study and is reported in Supplementary Table 4 page S8.

RESULTS

Literature Search and Study Selection

The study identification and selection process was conducted in accordance with the PRISMA 2020 guidelines. A total of 108 records were identified from three international databases: Scopus (n = 80), PubMed (n = 14), and ProQuest (n = 14). After removal of 21 duplicate records, 87 records remained for title and abstract screening, of which 47 were excluded. Forty reports were sought for retrieval, and three could not be retrieved. Consequently, 37 full-text reports were assessed for eligibility, and 22 reports were excluded because they did not meet the predefined eligibility criteria, including wrong intervention, wrong study design, wrong outcome, or other PICOS-related reasons. Ultimately, 15 studies were included in the qualitative synthesis, of which six provided sufficient quantitative data for inclusion in the meta-analysis. The complete study selection process is presented in Figure 1.

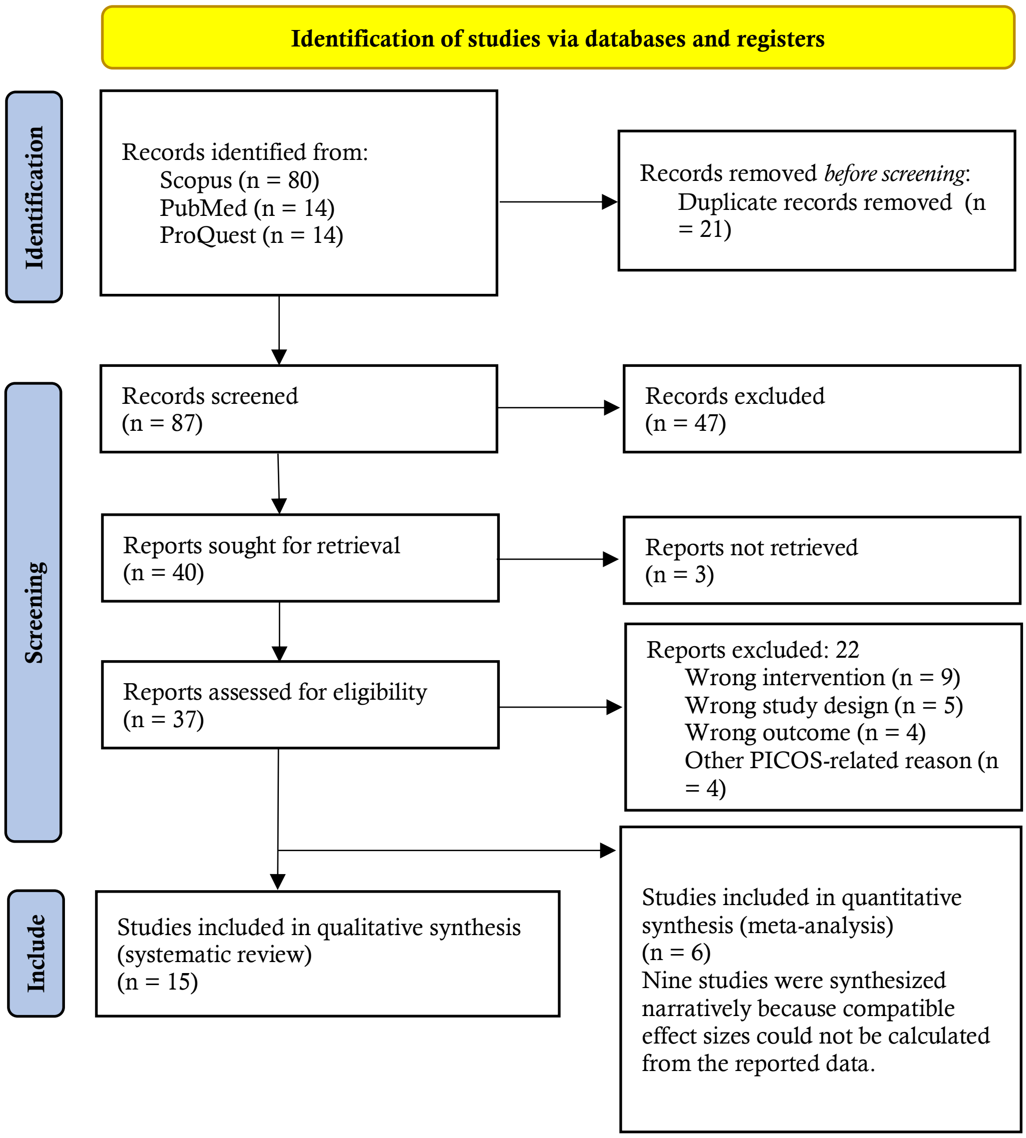


Figure 1. PRISMA Flowchart

Study Characteristics

Fifteen studies were included in the qualitative synthesis, representing the eligible evidence identified by this review on AI-supported motor performance and related learning outcomes in physical education and sport. The included studies originated from China, Taiwan, Japan, Poland, Saudi Arabia, Switzerland, and the United Kingdom.

The included studies comprised randomized controlled trials, quasi-experimental studies, and other controlled intervention designs evaluating AI-supported learning systems. The interventions included intelligent tutoring systems, motion-tracking technologies, computer vision, virtual reality, adaptive feedback systems, generative AI applications, and machine-learning-based movement recognition. Participants ranged from elementary school students to university students and sports trainees, with sample sizes ranging from 16 to 480 participants.

For descriptive synthesis, studies were mapped to conceptually distinct outcome domains, including skill acquisition, movement accuracy, sport-specific performance, motor proficiency, retention, and transfer. The primary quantitative synthesis was restricted to short-term post-intervention motor skill performance, including measures of skill execution, movement accuracy, sport-specific performance, and motor proficiency. Retention and transfer were not combined with the immediate performance meta-analysis and were interpreted separately. The mapping of each included study to its corresponding outcome domain is provided in Supplementary Table 3 page S4.

In addition to the primary outcome, several studies reported complementary learning-related outcomes, including learning motivation, engagement, self-efficacy, health literacy, learning interest, attitudes toward learning, and responses to AI-supported feedback. These secondary outcomes were synthesized narratively because they were measured with heterogeneous instruments and reported inconsistently across studies, rendering quantitative pooling inappropriate. The main characteristics of the included studies are presented in Table 1. The motor-performance outcome domain used for review classification is distinguished from other outcomes assessed; physical-fitness and complementary psychological or behavioral outcomes are reported descriptively but were not treated as direct measures of motor learning. The exact outcome selected for quantitative or qualitative synthesis is reported in Supplementary Table 3 page S4.

Table 1. Main Characteristics and Reported Outcomes of Included Studies

No	Authors & year	Country and Context	Research Objectives	Participants	AI/ML Technology	Research Design	Motor-Performance Outcome Domain	Outcomes assessed	Key Findings
1	Ma et al. (2025)	China; online university physical education (Baduanjin course)	Developing and evaluating an AI-based real-time feedback system using pose recognition to enhance motor learning in online physical education	70 non-PE students aged 18–20; final analysis included 60 participants (AI group n=28; control group n=32)	MediaPipe BlazePose, AI pose recognition, real-time feedback system, motion database, skeletal tracking	Randomized Controlled Trial (10 weeks; pre-post test with a MOOC control group)	Skill acquisition	Baduanjin skill score, movement quality, execution fluency, learning duration, learning interest, self-directed learning	The AI group achieved a higher total Baduanjin score than the control group (6.92±0.71 vs. 6.48±0.70; p=0.018). Significant improvements were also observed in movement quality and fluency. The AI group had a longer practice duration and showed increased interest in learning and greater self-directed learning. Mediation analysis indicated that the improvement in skills was primarily mediated by practice duration.

Continued Table 1

2	Rakha (2026)	Saudi Arabia; university physical education (handball course)	Evaluating the Effectiveness of ChatGPT-Based Digital Feedback in the Reciprocal Teaching Style (RTS) on	56 students in the Bachelor of Sport and Physical Activity Sciences program with no formal handball experience; experimental group n=28,	ChatGPT (GPT-4o free version), AI-generated corrective feedback, digital feedback system	Randomized Controlled Trial; pretest-posttest control group over 15 learning sessions spanning one semester	Skill acquisition	Passing, catching, dribbling, shooting, faking, defense, goalk	The ChatGPT group showed significant improvements in all handball skills compared to the control group (p <

			Improving Students' Basic Handball Skills and Attitudes	control group n=28				eeping	.001), with moderate to very large effect sizes (η^2 = .33–.87). The composite skill score was higher in the experimental group (2.85 ± 0.12 vs. 2.36 ± 0.07). The students also expressed positive attitudes toward using AI feedback.
3	Zhang (2025)	China; university physical education	Evaluating how AI-enhanced physical education improves students' motor skill acquisition, optimizes physiological load, and influences learning behavior patterns	480 undergraduate students; experimental group n=240 and control group n=240; ages 18–22	Motion capture system, machine learning, LSTM, VR, wearable sensors, AI adaptive feedback system	A 16-week mixed-methods experimental study; AI-supported PE group vs. traditional PE group	Skill acquisition	Basketball shooting skill acquisition, physiological load regulation, learning behavior patterns	AI-driven intervention increased the efficiency of skill mastery by 57.3% and reduced high-risk practice time by 78.9%. The rapid mastery group achieved proficiency more quickly (3.2 ± 0.8 weeks), whereas the delayed mastery group required additional EMG biofeedback. The AI adaptive system also increased the completion rate for passive learners by 37.2%.
4	Zhao et al. (2025)	China; physical education in elementary schools	Analyzing the Effect of AI-Integrated Sport Blended Learning (AI-SBL) on Elementary School Students' Athletic Skills and Learning Attitudes Compared to Traditional Face-to-Face Sport Learning (TFSL)	94 students aged 8–9 years; experimental group = 48, control group = 46	Exercise Load Monitoring System (ELMS), Daily Jump Rope App (DJR), AI-driven monitoring & feedback system	A 14-week quasi-experimental pretest-posttest study with an experimental and a control group	Motor proficiency.	Vital capacity, 50-meter run, sit-up-and-bend, 1-minute jump rope, sport attitudes	AI-SBL was significantly better than TFSL on all sports skill indicators ($p < 0.001$). Key findings: higher vital capacity, better 50-meter running times, increased flexibility, and higher jump rope performance in the AI-SBL group. Attitudes toward sports learning were also high and

Continued Table 1

									positive (mean 4.11–4.27).
5	Wu (2025)	China; physical education in high school	To investigate the impact of AI-enhanced dynamic physical education resources based on human-computer interaction on physical education learning compared to traditional methods.	120 students aged 12–18; 60 females and 60 males.	CNN-LSTM motion recognition, wearable sensors, computer vision, AR overlays, NLP, AI personalized recommendation system, real-time feedback system.	A 16-week randomized controlled crossover study comparing an AI-enhanced PE group with a traditional PE group.	Motor proficiency.	Physical fitness (VO_2 max, strength, flexibility), movement skill proficiency, engagement level, knowledge retention.	The AI group showed greater improvements than the traditional PE group in physical fitness (+23% vs. +12%), movement skill proficiency (+31% vs. +18%), knowledge retention (+27% vs. +15%), and engagement (+35% vs. +10%), with all results being statistically significant ($p < .01$). The system also received a high SUS usability score (84.3) and a satisfaction score of 4.7/5.
6	Xiao & Guo (2026)	China; physical fitness education at higher vocational colleges.	Investigating the integration of Generative Artificial Intelligence (GAI) through the PDGO (Precise Diagnosis–Dynamic Generation – Interactive Feedback–Iterative Optimization) model in physical fitness education for college students.	240 first-year students (120 in the experimental group; 120 in the control group).	GPT-4 for narrative generation, generative AI (GAI), pose estimation APIs, a wearable heart rate monitor, Polar H10, and an adaptive AI-feedback system.	Mixed-method 24-week quasi-experimental pretest-posttest control group design.	Motor proficiency	Motor skill proficiency in a physical fitness circuit using a 30-item analytical rubric.	The experimental group showed a 15.2% greater increase in motor skills than the control group, with an ANCOVA $F(1,237)=45.18$, $p<.001$, partial $\eta^2=.16$. Intrinsic motivation, situational interest, and health literacy also increased significantly.
7	Rauter et al. (2019)	Switzerland; robot-assisted rowing motor learning using a robotic rowing simulator.	To evaluate whether automated feedback selection in a robotic trainer can accelerate motor learning compared to a non-individualized feedback sequence.	16 healthy adult participants with no prior rowing experience; divided into an experimental group (n=8) and a control group (n=8).	Automated feedback selection, robotic trainer, augmented feedback, haptic guidance, DTW, human-robot interaction, adaptive feedback system.	Experimental motor learning study with control group and repeated measures.	Movement accuracy	Spatial error, velocity error, rowing movement accuracy, motor learning rate.	Both groups showed improvements in motor learning, but the experimental group exhibited a significantly higher learning rate for velocity error than the control group ($F_{1,14} = 5.275$, $p = 0.038$).

Continued Table 1

8	Harris et al. (2024)	United Kingdom; adaptive virtual reality-based golf putting training at the University of Exeter.	Testing the effectiveness of gaze-adaptive cues based on attention computing in improving visuomotor skill performance in virtual reality golf putting.	24 novice golfers (11 women, 13 men; average age 21 years) who were randomly assigned to the gaze-adaptive training group and the control group.	Attention computing, gaze-adaptive virtual reality, eye tracking, adaptive VR, immersive VR training.	Mixed experimental design with randomized group comparison, pre-test-post-test assessment, pressure condition, and real-world transfer test.	Movement accuracy; Transfer	Putting performance (radial error), quiet eye duration, gaze control, clubhead velocity, clubhead acceleration, visuomotor control.	Gaze-adaptive training significantly increased quiet eye duration in the experimental group (interaction β = 632.88, p < .001) and resulted in more expert-like kinematics. However, there was no significant improvement in putting accuracy or transfer to real-world performance.
9	Yan et al. (2024)	China; university physical education courses in several elective sports (volleyball, basketball, soccer, badminton, table tennis, aerobics).	To investigate the application of an intelligent sports tracking system to improve the effectiveness of physical education instruction at universities.	University physical education students; two classes were randomly selected for the experimental group and the control group. The sample size was not explicitly stated.	Machine vision-based intelligent motion tracking system, human motion tracking, particle filtering, VHMT algorithm, ARP motion model.	Quasi-experimental pretest-posttest control group design. The experimental group used an intelligent sports tracking system, while the control group used non-AI methods.	Skill acquisition	Motor skill levels in various sports: volleyball toss/pass, basketball shooting and dribbling, soccer dribbling and shooting, badminton serve, table tennis stroke, and aerobics performance.	Before the intervention, there were no significant differences between the experimental and control groups (P > 0.05). After the intervention, the entire experimental group showed a significant improvement compared to the control group (P < 0.05), with motor skill improvements ranging from 6.8% to 43.4%.
10	Qiu (2024)	China; badminton instruction for beginner college students.	Investigating the presence of hallucinations in Large Language Models (LLMs) during the learning of badminton motor skills and their impact on motor learning outcomes.	80 first-year students with no badminton experience; 40 in the Experimental Group (LLM-based self-learning using ChatGPT/New Bing) and 40 in the Control Group (learning with a badminton teacher or expert).	Large Language Models (ChatGPT and New Bing), AI-assisted self-guided motor learning.	A 16-week experimental study with a pretest-posttest control group; analysis was performed using a paired t-test and ANCOVA.	Skill acquisition	Badminton motor skills: clear, smash, footwork, and badminton-specific movement techniques.	Both groups showed improvements in motor skills (p<0.001), but the control group scored higher on the post-test for “clear” and “smash” than the LLM group. There were no significant differences in

									footwork. Hallucinations in the LLM group were primarily observed in explanations of the "forearm internal rotation swing," leading to misconceptions about the movement technique.
11	Tang (2024)	China; motor skills training for college students in the context of physical education.	To investigate the effectiveness of Virtual Reality (VR) technology in motor skills training using markerless optical motion capture and AI-based motion tracking.	120 non-physical education students from three parallel classes (traditional class, VR class, and video teaching class), with n=40 in each class.	Virtual Reality (VR), Mediapipe-based 3D human posture detection, motion tracking, AI-assisted motion capture.	A quasi-experimental pretest-posttest study with three learning groups over a 20-week period.	Skill acquisition	Academic interest, physical fitness, and motor skill training performance.	The VR group showed the greatest improvement compared to traditional classes and video-based instruction. Post-test scores increased by 0.56–14.86 points across various indicators, including motor skills. VR technology can improve movement accuracy, interest in learning, and motor skill performance.
12	Takita et al. (2025)	Japan; motor skills training using virtual reality co-embodiment with an AI instructor.	To investigate whether a virtual co-embodiment-based AI instructor can improve the efficiency of motor skill learning and skill retention compared to self-directed practice, human instructors, and recorded instructors.	84 participants in total (21 per condition). The 42 participants recruited for the newly added conditions included 22 men and 20 women (mean age 23.6 ± 3.04 years); the remaining participants were drawn from the previous experiment.	Artificial Intelligence, Long Short-Term Memory (LSTM), virtual reality, virtual co-embodiment, motion prediction model.	Randomized mixed-design experiment with four between-participant conditions (CoAI, CoHuman, CoRecord, and Alone) and repeated trials. Participants were randomly assigned to the four conditions; the CoHuman and Alone comparison data were drawn from the previous dataset reported by Kodama et al. [15]. Participants completed 10 practice trials and 3 post-	Skill acquisition; Retention	Improvement score, performance drop, hand distance, learner momentum contribution, motor skill retention.	CoAI resulted in greater improvement than training alone ($p < .05$) and better skill retention than CoHuman. Improvement in the test phase with CoAI was also greater than with Alone ($p < .001$) and comparable to that with a human instructor.

						practice test trials.			
13	Hsia et al. (2025)	Taiwan; yoga instruction in college physical education.	To determine the effectiveness of the SDT-based Gamified Intelligent Tutoring and Instant Feedback System (G-ITIFS) on yoga skill performance and learning engagement compared with the non-gamified C-ITIFS.	156 students aged 19–20; experimental group n=80 and control group n=76.	Artificial Intelligence, OpenPose, Intelligent Tutoring and Instant Feedback System (ITIFS), gamification, posture recognition, deep learning.	An 11-week quasi-experimental pretest-posttest control group design. The experimental group used the SDT-based G-ITIFS, while the comparator group used the non-gamified C-ITIFS, which was itself an AI-supported intelligent tutoring and feedback system.	Skill acquisition	Yoga skills performance, learning engagement, autonomy, competence, relatedness.	The experimental group showed higher yoga performance than the comparator group ($F = 9.87$, $p < .01$, $\eta^2 = .06$). Learning engagement was also higher, with a large effect size ($d = 1.11$).
14	Wojcik (2020)	Poland; motor learning for synchronized movements in rehabilitation, sports, and machine control.	Developing an automatic teaching system based on pattern recognition for learning coordinated and synchronized human movements.	16 students (2 women, 14 men; ages 22–25), divided into two experimental groups.	Machine learning, pattern recognition, k-NN model, MEMS inertial sensors, haptic/vibrotactile feedback, signal classification.	A comparative experiment of two AI-based motor learning methods: Mclass (classification-based adaptive teaching) vs. Msgv (single decision variable).	Movement accuracy	Hand-foot movement synchronization, phase error, trajectory control, coordination of periodic movements.	The Mclass method, which uses signal classification and adaptive selection of learning algorithms, demonstrates greater efficiency in teaching fast synchronized movements than the Msgv method.
15	Wójcik & Piekarczyk (2020)	Poland; movement training in sports, rehabilitation, and professional work skills.	To evaluate the effectiveness of an adaptive machine learning-based automatic motion learning system that uses motion signal classification to select the appropriate teaching algorithm.	18 students majoring in Automation and Robotics (4 women, 14 men), aged 22–25 years, randomly allocated to two groups of equal size (n = 9 per group).	Machine learning classification (kNNModel, HMM comparison), MEMS inertial sensors, vibrotactile feedback, adaptive motor learning system.	Randomized two-group experimental study comparing an adaptive classification-based teaching method with a fixed-algorithm teaching method..	Skill transfer	Motor learning accuracy, movement deviation, motion timing, transfer of skill, RMS E-based movement quality.	An adaptive system based on signal classification demonstrates greater effectiveness in motor learning than a system without signal classification. Statistical tests confirm an improvement in the quality of motor learning.

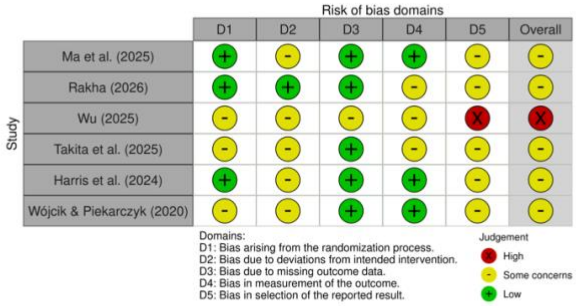
Note. The 'Motor-Performance Outcome Domain' column identifies the domain used for review classification. The 'Outcomes Assessed' column reports all relevant outcomes described in the original studies. General physical-fitness outcomes and complementary psychological or behavioral outcomes were not considered direct measures of motor learning. The exact variable selected for synthesis is reported in Supplementary Table 3 page S4.

Risk of Bias Assessment

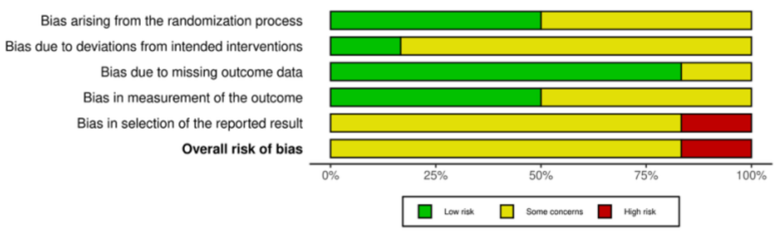
Methodological quality was assessed using the Cochrane Risk of Bias 2 (RoB 2) tool for randomized controlled trials (RCTs) and ROBINS-I for non-randomized intervention studies. Among the five randomized controlled trials, one study (20%) was judged as having a high risk of bias, whereas four studies (80%) presented some concerns. Among the ten non-randomized studies, seven (70%) were rated as having a moderate risk of bias and three (30%) as having a serious risk of bias. No study was judged as having a critical risk of bias. In the ROBINS-I assessment, the domains most frequently associated with elevated risk were confounding, deviations from intended interventions, and selection of the reported result. Serious risk was concentrated primarily in the confounding domain. In the RoB 2 assessment, concerns most commonly related to deviations from intended interventions and selection of the reported result.. Detailed study-specific domain-level judgments for RoB 2 and ROBINS-I are provided in Supplementary Tables 5a and 5b page S9-S10.

Among non-randomized studies, overall risk of bias ranged from moderate to serious. Elevated domain-level risk was particularly frequent for confounding, deviations from intended interventions, and selection of the reported result.” A higher risk of bias was generally found in quasi-experimental studies that did not use full randomization and had limited control over external variables. Visualizations of the risk-of-bias assessment results using traffic-light plots and summary plots are presented in Figures 2 and 3.

Figure 2 shows that most randomized controlled trials were judged as having some concerns regarding overall risk of bias, while one study was classified as having a high risk of bias. The domains contributing most frequently to potential bias were deviations from intended interventions and selection of the reported result. Figure 3 indicates that most non-randomized studies were judged as having a moderate overall risk of bias (7/10), whereas three studies were classified as having a serious risk of bias. The domains most frequently associated with elevated risk were confounding, deviations from intended interventions, and selection of reported results. No study was judged as having a critical risk of bias. Study-specific domain-level and overall judgments for RoB 2 and ROBINS-I are provided in Supplementary Tables 5a and 5b page S9-S10.

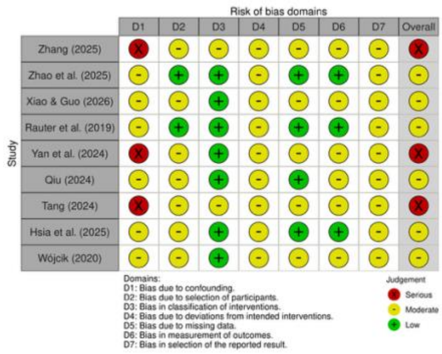


(a)

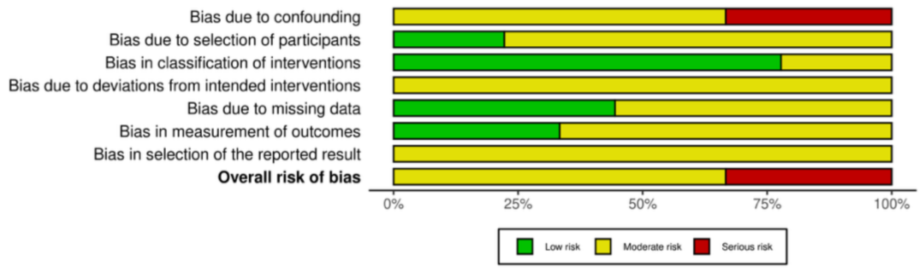


(b)

Figure 2. Visualization of the results of the risk of bias assessment for randomized controlled trials (RCTs) using RoB 2. (a) Traffic light plot showing the risk of bias for each study based on the five RoB 2 domains. (b) Summary plot showing the proportion of risk of bias in each assessment domain.



(a)



(b)

Figure 3. Visualization of the results of the risk of bias assessment for non-randomized studies using ROBINS-I. (a) Traffic-light plot showing the risk of bias for each study across the seven ROBINS-I domains. (b) Summary plot showing the proportion of risk of bias in each assessment domain.

Qualitative Synthesis of AI-Supported Motor Skill Performance and Related Outcomes

3.1 AI-Based Feedback Systems and Adaptive Learning

One of the most frequently reported applications of AI in motor learning involves providing real-time feedback and adaptive learning support. Several studies reported better short-term motor performance under AI-supported feedback conditions, although the designs do not establish a uniform effect across settings. Ma et al. (2025) reported that an AI pose-recognition system significantly enhanced Baduanjin skill performance, movement quality, execution fluency, and learning interest compared with conventional online instruction. Similarly, Rakha (2026) found that ChatGPT-generated digital feedback substantially improved handball skills, including passing, dribbling, shooting, and defensive performance, while also promoting positive student attitudes toward learning. Hsia et al. (2025) demonstrated that a gamified intelligent tutoring system with instant feedback significantly improved yoga skill performance and learning engagement compared with the non-gamified C-ITIFS comparator, which itself provided intelligent tutoring and feedback. In addition, Rauter et al. (2019) showed that automated feedback selection in a robotic rowing trainer accelerated motor learning rates by optimizing the timing and content of augmented feedback. Collectively, these findings suggest that AI-based feedback systems may support short-term motor performance through immediate error information, individualized practice adaptation, and continuous performance monitoring; durable learning cannot be inferred from immediate performance alone.

3.2 Computer Vision and Motion Tracking Technologies

Another major research theme involved the application of computer vision, intelligent motion-tracking systems, and AI-assisted performance analysis to support motor skill development. Hsia et al. (2025) demonstrated that an AI-assisted intelligent tutoring and feedback system improved learners' movement performance, while Tang (2024) and Xiao & Guo (2026) reported substantial improvements in sport-specific motor skill execution using AI-supported visual analysis and intelligent feedback. Similarly, Zhao et al. (2025), Ma et al. (2025), and Rakha (2026) showed positive effects of AI-assisted instructional systems on motor skill performance. Across the included studies, AI technologies employed computer vision, intelligent feedback, machine learning, and motion analysis to provide objective assessment and individualized feedback that supported movement refinement. Collectively, these findings suggest that AI-based movement-analysis technologies may support short-term motor skill performance in physical education and sport, although the magnitude and generalizability of benefit remain uncertain across intervention designs, learner groups, and outcome measures.

3.3 Virtual Reality and Immersive Learning Environments

Virtual Reality (VR) represents another prominent AI-supported approach for facilitating motor learning. By creating immersive and interactive learning environments, VR systems allow learners to practice complex motor skills under controlled conditions while receiving immediate feedback on their performance. Tang (2024) reported that AI-assisted VR training significantly improved motor skill performance, movement accuracy, and learning interest compared with traditional instruction and video-based learning. Similarly, Takita et al. (2025) demonstrated that AI-powered virtual co-embodiment instructors enhanced motor skill acquisition and retention compared with self-directed practice. Harris et al. (2024) further showed that gaze-adaptive VR training improved visuomotor control and attentional performance, although improvements in real-world putting accuracy were limited. Overall, these findings suggest that AI-supported immersive environments may support short-term motor performance and engagement, but evidence for real-world transfer remains limited.

3.4 Generative Artificial Intelligence and Large Language Models

Recent studies have also explored the use of Generative Artificial Intelligence (GAI) and Large Language Models (LLMs) in motor learning contexts. Unlike traditional feedback systems, generative AI can provide personalized explanations, learning guidance, and adaptive instructional support through natural language interactions. Rakha (2026) demonstrated that ChatGPT-generated feedback enhanced handball skill performance and learner attitudes. Similarly, Xiao & Guo (2026) reported that a Generative AI-supported instructional model significantly improved physical fitness-related motor skills, intrinsic motivation, and health literacy among college students. However, evidence also indicates potential limitations. Qiu (2024) found that although students using LLM-supported learning improved their badminton skills, the instructor-led group achieved superior outcomes on several performance indicators. The study further identified hallucination-related inaccuracies in AI-generated explanations, which occasionally led to misconceptions about movement. These findings suggest that while generative AI offers promising opportunities for personalized motor learning, human supervision remains essential to ensure instructional accuracy and prevent the transmission of incorrect movement information.

3.5 Complementary Learning-Related Outcomes

Beyond motor skill performance, numerous studies reported improvements in psychological and behavioral outcomes associated with learning. AI-supported interventions were linked to increased learning engagement, motivation, learning interest, self-directed learning, positive attitudes toward physical education, and health-related literacy. Hsia et al. (2025) and Wu (2025) reported substantial gains in learner engagement following AI-supported instruction. Ma et al. (2025) observed increased interest in learning and self-directed learning behaviors, whereas Rakha (2026) and Zhao et al. (2025) identified positive student attitudes toward AI-enhanced physical education. Xiao & Guo (2026) additionally reported improvements in intrinsic motivation and health literacy. These findings indicate that AI-supported interventions may influence motivational and behavioral conditions relevant to sustained participation and continued practice; however, these outcomes are complementary and should not be interpreted as direct measures of motor learning.

Across the included studies, three recurring mechanisms were proposed as potential contributors to AI-supported motor performance: real-time augmented feedback, individualized practice adaptation, and continuous performance monitoring. These mechanisms align with motor learning principles emphasizing feedback, error correction, and optimized practice conditions. However, evidence for retention and transfer was sparse and was not pooled; these outcomes were interpreted separately from immediate post-intervention performance.

Quantitative Synthesis

The pooled primary outcome was short-term motor skill performance, encompassing immediate post-intervention measures of skill execution, movement accuracy, sport-specific performance, and motor proficiency. Retention and transfer outcomes were not included in this pooled estimate.

Six study-level comparisons comprising 686 participants contributed to the quantitative synthesis. For Tang (2024), which included three parallel groups, the meta-analytic contrast compared the virtual reality class with the traditional lecture class; the video-teaching class was not included in the primary quantitative contrast. Because comparator conditions varied and at least one contrast compared two AI-supported systems, the model should be interpreted as pooling designated experimental-versus-comparator contrasts rather than as a simple AI-versus-no-AI comparison.

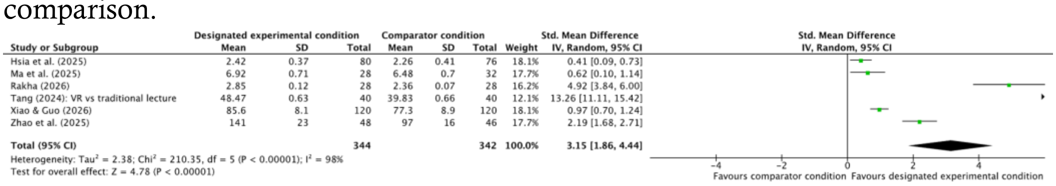


Figure 4. Forest plot comparing the designated AI-supported experimental conditions with comparator conditions for short-term motor skill performance using a random-effects model (Hedges' g SMD, 95% CI). Positive values favor the designated experimental condition. The study identities, outcomes, sample sizes, means, standard deviations, and effect directions correspond to the quantitative dataset used for the analysis and Supplementary Tables 2–4 page S3-S8. For Tang (2024), the quantitative contrast compared the virtual reality class with the traditional lecture class; the video-teaching arm was not included in the meta-analysis.

Across the six study-level comparisons included in the meta-analysis, data from 686 participants were analyzed, comprising 344 participants in the designated AI-supported experimental conditions and 342 participants in the comparator conditions (Figure 4). Using a random-effects model, the designated experimental conditions showed higher short-term motor skill performance than the comparator conditions (SMD = 3.15, 95% CI 1.86–4.44, $Z = 4.78$, $p < .001$). Very high between-study heterogeneity was observed ($\tau^2 = 2.38$; $\chi^2 = 210.35$, df = 5, $p < .001$; $I^2 = 98\%$), indicating marked variability in effect estimates across the included studies. All six individual comparisons favored the designated experimental condition, but the magnitude of effect varied substantially.

Table 2. Targeted Influence Analyses

Analysis	Studies	SMD (95% CI)	I^2
Primary analysis	6	3.15 (1.86–4.44)	98%
Excluding Tang	5	1.68 (0.78–2.59)	95%
Excluding Rakha	5	2.70 (1.43–3.97)	98%
Excluding Tang & Rakha	4	1.03 (0.38–1.68)	91%

A complete leave-one-out sensitivity analysis is reported in Supplementary Table 4 page S8. Across all six leave-one-out iterations, pooled estimates remained positive; the largest reduction occurred when Tang (2024) was omitted (SMD = 1.68, 95% CI 0.78–2.59), with heterogeneity remaining very high ($I^2 = 95\%$). Table 2 additionally highlights targeted influence analyses for Tang (2024), Rakha (2026), and both studies together. These analyses show that the magnitude of the pooled estimate is sensitive to influential studies even though the direction remains positive; very high heterogeneity persisted across the targeted analyses ($I^2 = 91$–98%).

DISCUSSION

The present study evaluated AI-supported interventions in relation to motor skill performance in physical education and sport settings. The quantitative synthesis favored the designated experimental conditions over active or conventional comparator conditions (SMD = 3.15, 95% CI 1.86–4.44), but the pooled magnitude is highly uncertain because only six studies were included and between-study heterogeneity was very high ($I^2 = 98\%$). The qualitative synthesis reported favorable patterns in short-term motor performance and in complementary outcomes such as engagement, motivation, self-directed learning, and attitudes. Taken together, the findings support cautious consideration of AI as a pedagogical adjunct while providing limited evidence about durable motor learning, retention, or transfer.

AI-Supported Interventions May Improve Short-Term Motor Skill Performance

The pooled analysis suggests that designated AI-supported experimental conditions may improve short-term motor skill performance relative to their comparator conditions. However, the quantitative synthesis included only six studies and showed very high heterogeneity (SMD = 3.15, 95% CI 1.86–4.44; $I^2 = 98\%$). The pooled magnitude is unusually large and is strongly influenced by at least one extreme study-level effect, so it should not be interpreted literally as a typical effect expected across physical education or sport settings. Comparator conditions also differed across studies, including an active AI-supported comparator, further limiting any simple interpretation of the estimate as AI versus conventional instruction.

The findings are consistent with previous educational AI research demonstrating that adaptive learning systems improve learning outcomes by tailoring instruction to individual learner needs (Kakish, 2024; Sari et al., 2024; Yekollu et al., 2024). In motor learning contexts, personalization appears particularly important because learners progress at different rates and often require specific corrective feedback to refine movement patterns. Technologies such as pose estimation, computer vision, motion tracking, and intelligent tutoring systems enable the delivery of individualized instruction that would be difficult to achieve consistently in traditional physical education settings (Ashwin et al., 2023; Romano et al., 2025), particularly in large classes.

Several studies also reported differences in practice exposure and feedback opportunities under AI-supported conditions. For example, learners receiving AI-generated feedback tended to spend more time practicing, engaged more frequently with learning materials, and received more opportunities for performance correction (Halkiopoulos & Gkintoni, 2024; Harris et al., 2024; Lauber & Keller, 2014; Rauter et al., 2019). Such mechanisms are plausible, but they were not tested as cross-study mediators and therefore should not be used to explain the pooled effect causally.

The pooled result should also be interpreted in light of methodological quality. Most randomized controlled trials were judged to present some concerns, while several non-randomized studies had moderate or serious risk of bias, with recurrent domain-level concerns related to confounding, deviations from intended interventions, and selection of the reported result. These limitations, together with the very high heterogeneity, make the magnitude of the pooled effect uncertain across educational settings, intervention types, and learner populations. The quantitative estimate should therefore be viewed as exploratory rather than as a precise estimate of a general AI effect.

Interpreting the Findings Through Motor Learning Theory

The present findings can be understood through the perspective of Motor Learning Theory, which emphasizes practice, feedback, error correction, and adaptation as fundamental mechanisms underlying skill acquisition (Wulf & Lewthwaite, 2016). According to contemporary motor learning frameworks, augmented feedback plays a critical role in helping learners identify discrepancies between intended and actual movement outcomes. AI-supported systems that monitor movement and return corrective information can function as forms of augmented feedback by providing performance-relevant information in real time (Dyer et al., 2015; Lauber & Keller, 2014).

Across the included studies, three recurring mechanisms emerged: real-time augmented feedback, individualized practice adaptation, and continuous performance monitoring. These mechanisms closely align with established motor learning principles. Real-time feedback enables immediate correction of movement errors before maladaptive patterns become stabilized. Individualized adaptation ensures that task difficulty and instructional support remain aligned with learner capabilities, promoting optimal challenge conditions (Ma et al., 2025). Continuous monitoring allows learners to observe progress over time and make evidence-based adjustments to their performance.

From the perspective of the OPTIMAL Theory of Motor Learning, AI may also enhance learning by increasing perceived competence and motivation (Wulf & Lewthwaite, 2016). Several studies reported improvements in engagement, learning interest, intrinsic motivation, and positive attitudes toward physical education (Calderón et al., 2020; Maberah et al., 2025; Yang, 2024). These psychological outcomes may support conditions that encourage continued practice and engagement, but they are not direct evidence of motor learning. Accordingly, motivational and biomechanical pathways should be treated as plausible mechanisms rather than established explanations of the pooled performance effect.

Interpreting the Very High Heterogeneity

The meta-analysis showed very high heterogeneity ($I^2 = 98\%$), indicating that the size of the experimental-versus-comparator contrast varied markedly across studies. The leave-one-out analyses reduced the pooled magnitude in some iterations but did not resolve the heterogeneity, suggesting that no single study fully explains the observed variability.

Several sources of heterogeneity are plausible. The pooled studies differed in AI modality, participant age and experience, intervention duration, educational setting, comparator condition, and the construct and scale used to assess performance. The six pooled outcomes included Baduanjin skill, composite handball skills, one-minute jump-rope performance, a physical-fitness motor-proficiency rubric, a motor-training performance score, and yoga performance. These measures are standardized statistically but are not interchangeable in substantive meaning. In addition, one pooled comparison contrasted two AI-supported tutoring systems rather than AI with a non-AI control. This diversity limits the interpretation of a single pooled SMD as a common effect across contexts.

Finally, intervention duration varied considerably, ranging from short-term experimental training sessions to semester-long educational programs. Although intervention duration may contribute to between-study differences, the present review could not test this moderator because only six studies were pooled (Lauber & Keller, 2014; Rauter et al., 2019; Vandevoorde et al., 2022). Accordingly, the pooled estimate should be interpreted as an average across substantially different interventions rather than as a common effect expected in a specific physical education or sport context.

Why Did Some Studies Report Less Positive Results?

Although most studies demonstrated favorable outcomes, not all findings were uniformly positive. The study conducted by Qiu (2024) provides an important example. While learners using Large Language Models (LLMs) improved their badminton skills, the instructor-led group achieved superior performance on several outcome measures. Furthermore, the study identified hallucination-related inaccuracies in AI-generated explanations that occasionally led to misconceptions about movement.

These findings highlight an important distinction between AI-assisted learning and expert-guided motor instruction. Motor learning often requires highly precise biomechanical feedback, contextual judgment, and nuanced movement correction (Gao & Chen, 2025; Huang et al., 2026). Current generative AI systems may occasionally produce inaccurate or oversimplified explanations, particularly when interpreting complex movement mechanics. Rather than replacing teachers or coaches, AI should be viewed as a complementary pedagogical technology that supports individualized feedback, continuous performance monitoring, and evidence-informed motor instruction.

Interestingly, the less favorable findings also reinforce the importance of human oversight in AI-supported learning environments. Hybrid models that combine AI-generated feedback with teacher expertise may represent a particularly promising instructional approach, as they integrate technological scalability with professional pedagogical judgment.

Practical Implications for Physical Education and Sports Coaching

The findings of this review have several practical implications for educators, coaches, and policymakers. First, AI technologies may help address one of the most persistent challenges in physical education: providing individualized feedback in large classes. Automated movement analysis systems can support teachers by identifying learner errors and generating immediate corrective suggestions, thereby extending instructional capacity.

Second, AI-supported systems may facilitate differentiated instruction by adapting learning tasks to individual performance levels. Such personalization could be particularly valuable for learners with varying motor abilities, beginners requiring additional support, and students with special educational needs.

Third, AI technologies may provide coaches and practitioners with objective movement assessment and performance-monitoring information. Such information may assist instructional or coaching decisions, but the present review does not establish effects on training-load optimization, injury prevention, or the overall efficiency of skill-development programs; these outcomes should therefore not be inferred from the pooled motor-performance findings.

However, implementation should be guided by pedagogical principles rather than technological novelty. The effectiveness of AI depends not only on technological sophistication but also on the quality of instructional design and the integration of meaningful feedback within the learning process. Successful implementation, therefore, depends on integrating AI into sound pedagogical practice and maintaining active involvement from teachers and coaches throughout the learning process.

LIMITATIONS OF THE STUDY

This review has several limitations that should be considered when interpreting the findings. First, although fifteen studies were included in the qualitative synthesis, only six provided compatible quantitative data for meta-analysis. Consequently, the pooled estimate is based on a small evidence base, and subgroup analysis, meta-regression, publication-bias assessment, and formal small-study-effect testing could not be performed.

Second, very high between-study heterogeneity (I^2 = 98%) was observed, reflecting differences in participants, AI technologies, intervention duration, educational settings, comparator conditions, and motor-performance measures. The largest reduction in the pooled effect occurred after exclusion of Tang (2024), yet heterogeneity remained very high (I^2 = 95%), indicating that the pooled magnitude is both influential-study sensitive and broadly heterogeneous. In addition, at least one pooled contrast used an active AI-supported comparator, so the meta-analysis should not be interpreted as estimating a homogeneous AI-versus-non-AI effect.

Third, the methodological quality of the included studies varied considerably. Several studies employed quasi-experimental or non-randomized designs and were judged as having moderate or serious risk of bias, particularly because of confounding and selective reporting. Therefore, causal inferences regarding the effectiveness of AI-supported interventions should be interpreted cautiously.

Fourth, the literature search was limited to Scopus, PubMed, and ProQuest and to English-language, peer-reviewed journal articles published from 2015 to 2026. Relevant studies indexed primarily in specialist sport science, education, engineering, or computer science databases, as well as non-English or grey literature, may therefore have been missed.

Finally, artificial intelligence is a rapidly evolving field. Consequently, the technologies evaluated in the included studies may not fully represent current or future AI applications in physical education and sport, potentially limiting the long-term applicability of the present findings.

Future Research Directions

Future research should move beyond asking whether AI improves immediate performance and instead determine which AI-supported approaches improve short-term motor skill performance, whether those gains are retained and transferred, for whom they are effective, and under what instructional conditions. Larger randomized controlled trials with clearly defined comparators, standardized motor-performance measures, and prespecified retention and transfer assessments are needed.

Future studies should also compare different categories of AI technologies, including computer vision systems, intelligent tutoring systems, virtual reality environments, wearable sensor platforms, and generative AI applications. Such comparisons help identify which technologies provide the greatest educational value for specific motor learning objectives.

Additionally, researchers should examine long-term retention, skill transfer, and real-world performance outcomes rather than relying solely on immediate post-intervention assessments. Understanding whether AI-supported gains persist over time remains an important unanswered question.

Finally, future investigations should explore hybrid instructional models that combine AI-generated feedback with teacher expertise. Such approaches may maximize the benefits of technological innovation while minimizing potential risks associated with inaccurate or incomplete AI-generated guidance.

CONCLUSIONS

This systematic review and meta-analysis suggests that designated AI-supported experimental conditions may improve short-term motor skill performance in physical education and sport settings, but the magnitude of benefit is uncertain. The pooled estimate was large (SMD = 3.15) and statistically significant, yet it was derived from only six studies, was accompanied by very high heterogeneity (I^2 = 98%), and was sensitive to influential study-level effects. Moreover, comparator conditions were not uniform, and at least one comparison contrasted two AI-supported systems. Most studies assessed immediate post-intervention performance rather than delayed retention or transfer; the findings therefore should not be interpreted as definitive evidence of durable motor learning. AI is best viewed as a complementary pedagogical tool that may extend feedback and monitoring capacity while preserving the central role of teachers and coaches. Future trials should use transparent reporting, clearly specified comparators, standardized outcomes, and retention and transfer assessments.

AI DISCLOSURE STATEMENT

During the preparation and revision of this manuscript, the authors used DeepL Translate, Google Translate, Grammarly, and OpenAI's ChatGPT to support translation, language refinement, and consistency checking. All AI-assisted outputs and editorial suggestions were critically reviewed and revised by the authors, who take full responsibility for the accuracy, interpretation, and content of the manuscript.

DATA AVAILABILITY

Materials supporting this review, including the final data extraction sheet, database-specific search strategies, screening and deduplication records, full-text exclusion list with reasons, domain-level RoB 2 and ROBINS-I judgments, RevMan analysis files, and supplementary materials, are available through the Open Science Framework (OSF) repository at https://doi.org/10.17605/OSF.IO/KWGZ7.

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CONFLICT OF INTEREST

Yulingga Nanda Hanief serves as Director of CV. Rezki Media, the publisher of the journal in which this article is published. To maintain editorial independence and avoid any potential conflict of interest, the author was not involved in the editorial decision-making or peer-review process for this manuscript. The other authors declare no conflicts of interest.

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