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Paper review
Pregledni rad

Use of AI Technology Training on Motor Parameters: Systematic review

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Abstract: *The aim of this systematic review was to examine the use of AI training technology on motor performance. The research was conducted according to the PRISMA guidelines, using the PICOS framework for study selection, and the search included relevant databases such as PubMed, Web of Science, Scopus, MEDLINE, ERIC and Google Scholar. The final analysis included 16 studies that met strict methodological relevance criteria, and quality was assessed using the PEDro scale. Analysis of the included studies indicates that the most effective programs lasted between 5 and 8 weeks, with a frequency of at least three training sessions per week, while more significant effects were observed with interventions that included personalized feedback and adaptive algorithms. AI systems have shown the potential to improve strength, flexibility, coordination and other motor parameters, providing precise, individualized feedback. Although the results are promising, the variable methodological quality and heterogeneity of the technologies used indicate the need for further research in real-world sports conditions.*

Keywords: *Artificial intelligence, Physical training, Motor fitness, Exercise, Digital coaching, Robotics.*

Introduction

Wearable technology, such as electronic devices with wireless communication such as clothing on the body, equipment or accessories containing sensors for monitoring physiological and motor functions, is increasingly on the rise (Ometov et al., 2021). The value of 40.65 billion dollars in 2020 is an indicator of the attractiveness of this technology, with an expected growth of 13.8% by 2028 (Svertoka et al., 2021). A wide range of applications in the fields of sports medicine and training as well as low costs are just some of the benefits.

The emergence and development of AI technology has led to significant changes in the sports context. Wearable devices allow for precise measurement of parameters, optimization of training, and better insight into conditions such as heart rate, blood pressure, body temperature, EEG, ECG, as well as movement speed and acceleration (Altini et al., 2021; de Zambotti et al., 2019). For example, the Oura ring has proven to be a very reliable tool for sleep monitoring, while smartwatches such as the Apple Watch, through the Apple Health app, participate in the Apple Heart and Movement Study and the Apple Hearing Study (Turakhia et al., 2019).

The amount of data generated by these devices and processed using artificial intelligence (AI) has proven to be very effective and applicable. Russell and Norvig defined artificial intelligence as the design and construction of intelligent agents that receive instructions from the environment and take actions that affect that same environment (Helm et al., 2020). Machine learning in sports practice allows the system to "learn" and absorb knowledge from data in order to improve athlete performance (Estava et al., 2019). It has proven very effective as learning has already been applied in medical sciences in diagnostics as well as in disease monitoring (Vandevoorde et al., 2022).

In the fields of sports medicine, the most common application of sensors is for injury prevention, risk assessment, performance optimization and motor skills improvement, and if there is huge potential, there is still a lack of concise works that connect artificial intelligence and wearable technology in sports practice.

In addition, AI systems that function as digital assistants in motor learning are increasingly being used, using algorithms to recognize patterns in movements and analyze complex biomechanical parameters (Vandevoorde et al., 2022). These systems, when connected to wearable devices and sensors, enable advanced forms of individualization of training, as well as the identification of potential errors in the performance of motor tasks (Chidambaram et al., 2022). In the teaching context, the implementation of AI technology contributes to more efficient learning and more precise execution of exercises, which is especially important in higher education sports education (Fu, 2020). Also, digital sports applications driven by artificial intelligence offer users the possibility of continuous progress monitoring, automated feedback and injury risk prediction, which further contribute to the optimization of training (Bodemer, 2023; Hajder et al., 2025). However, this technology requires additional research to address all the challenges and ethical dilemmas that accompany its increasingly intensive application (Bodemer, 2023).

The aim of the research is to examine the use of AI training technology on motor performance.

Method

For research purposes, PRISMA guidelines (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) were applied.

Literature search strategy

An electronic search was conducted in multiple scientific databases, including PubMed, Web of Science, Scopus, MEDLINE, ERIC, and Google Scholar, as well as in relevant grey literature related to the application of artificial intelligence in the context of physical exercise and motor fitness. Recent papers published between 2020 and 2025 were analyzed.

The keyword combination used for the search included the phrases: "artificial intelligence" AND "physical training" OR "motor fitness" OR "exercise" AND "digital coaching" NOT "robotics", with the use of logical operators to narrow the search scope. Specific keywords included: AI fitness coaching, motor skill improvement, digital personal trainer, intelligent feedback systems, and automated posture correction.

Only papers published in English were considered. Conference abstracts, preprints, and papers that had not passed the peer review process were excluded from the analysis in order to preserve scientific relevance and methodological consistency.

Titles and abstracts of papers were first screened for relevance, after which studies that met the previously defined inclusion criteria underwent a detailed content analysis. When necessary, the authors consulted with each other about the inclusion of certain studies in the research.

Criteria for inclusion and exclusion of studies

To ensure objectivity in the selection of papers, three authors (BB, Đ.H., RP) independently assessed the studies according to predefined criteria, using the PICOS framework (Population, Intervention, Comparators, Outcomes and Study Design). Only papers that:

- have as their topic the application of AI technologies in the context of physical exercise or motor fitness,
- contain clearly described interventions aimed at improving motor fitness,
- use measurable indicators of progress,
- papers published in peer-reviewed scientific journals

Papers that focus exclusively on passive technologies (e.g., robotic assistance without a training component) were excluded, as were studies that did not include human subjects or did not have clearly defined methodological approaches.

A total of 16 studies that met all of the above criteria were included in the analysis. The PICOS model was used in this paper to systematically define the inclusion and exclusion criteria for studies, thus ensuring methodological clarity and consistency in the selection of relevant studies. This approach allows for precise structuring of the population, interventions, comparators, outcomes, and study design within the analysis of the impact of AI technologies on motor fitness.

Table 1. The inclusion and exclusion criteria used according to the PICOS model

PICOS category	Inclusion criteria	Exclusion criteria
P (Population)	People of both sexes, regardless of age, level of physical activity or health status; including recreational users, athletes, students and clinical groups.	People with serious health conditions or injuries that prevent them from performing physical activity.
And (Intervention)	Studies that used AI technologies in training – including virtual assistants, chatbot trainers, algorithms for posture correction, program personalization, and fatigue management; measurements performed through sensors, video analysis, and applications.	Studies that did not use any form of artificial intelligence; works that relied solely on self-reported physical activity without objective verification; interventions that did not have a physical component.
C (Comparators)	Studies comparing an experimental group (AI intervention) with a control group or other digital training modalities (e.g. classic online training vs. AI training).	Comparisons between unrelated sports or populations (e.g., soccer players vs. handball players); studies without a clear comparator.
About (Outcomes)	Changes in motor fitness: coordination, strength, flexibility, balance, precision; posture correction; increased physical activity; motivation; positive effects on mental health.	Studies that did not perform or report specific intervention outcomes; imprecise or incomplete outcomes.
With (Study design)	Randomized and non-randomized controlled studies; experimental and quasi-experimental research; research published in English or Serbian in peer-reviewed journals between 2010 and 2024.	Duplicates; conference abstracts; case reports with <5 participants per group; review papers; preprint versions; studies outside the given timeframe or in languages other than Serbian or English.

Study selection and assessment of methodological quality

Screening and data extraction were performed by three authors (BB, Đ.H., RP) in accordance with the previously described search strategy. EndNote was used for reference management, while Mendeley Reference Manager (version 2.111.0, Copyright © 2024 Elsevier Ltd., Barcelona, Spain) was used for duplicate detection. The quality of the included studies was critically assessed, with systematic identification of potential limitations such as: small sample sizes, limited application of AI tools, as well as differences in the type of technology used and measurement instruments. Given the pronounced heterogeneity among the studies, a qualitative approach was applied to analyze their characteristics, while meta-analysis was not feasible.

The study used a descriptive method, and the methodological quality of the selected papers was independently assessed by three researchers using the PEDro scale (Physiotherapy Evidence Database), which contains 11 assessment criteria. Each criterion was scored binary (1 = met, 0 = not met). Studies that achieved 6 or more points were rated as high-quality, those with 4 to 5 points as medium quality, while studies with less than 4 points were classified as low quality.

Results

Literature search

The process of data collection, analysis, and study elimination is shown in Figure 1. An initial search of the selected databases identified 417 potential studies. After removing duplicates, reviewing titles and abstracts, and applying the defined exclusion criteria, 47 studies were included in the analysis. A more detailed assessment of eligibility further excluded some of the studies, reducing the total number of studies meeting the predefined inclusion criteria to 16. The final number of included studies forms the basis for this systematic review, and the complete selection and analysis procedure is shown in Figure 1.

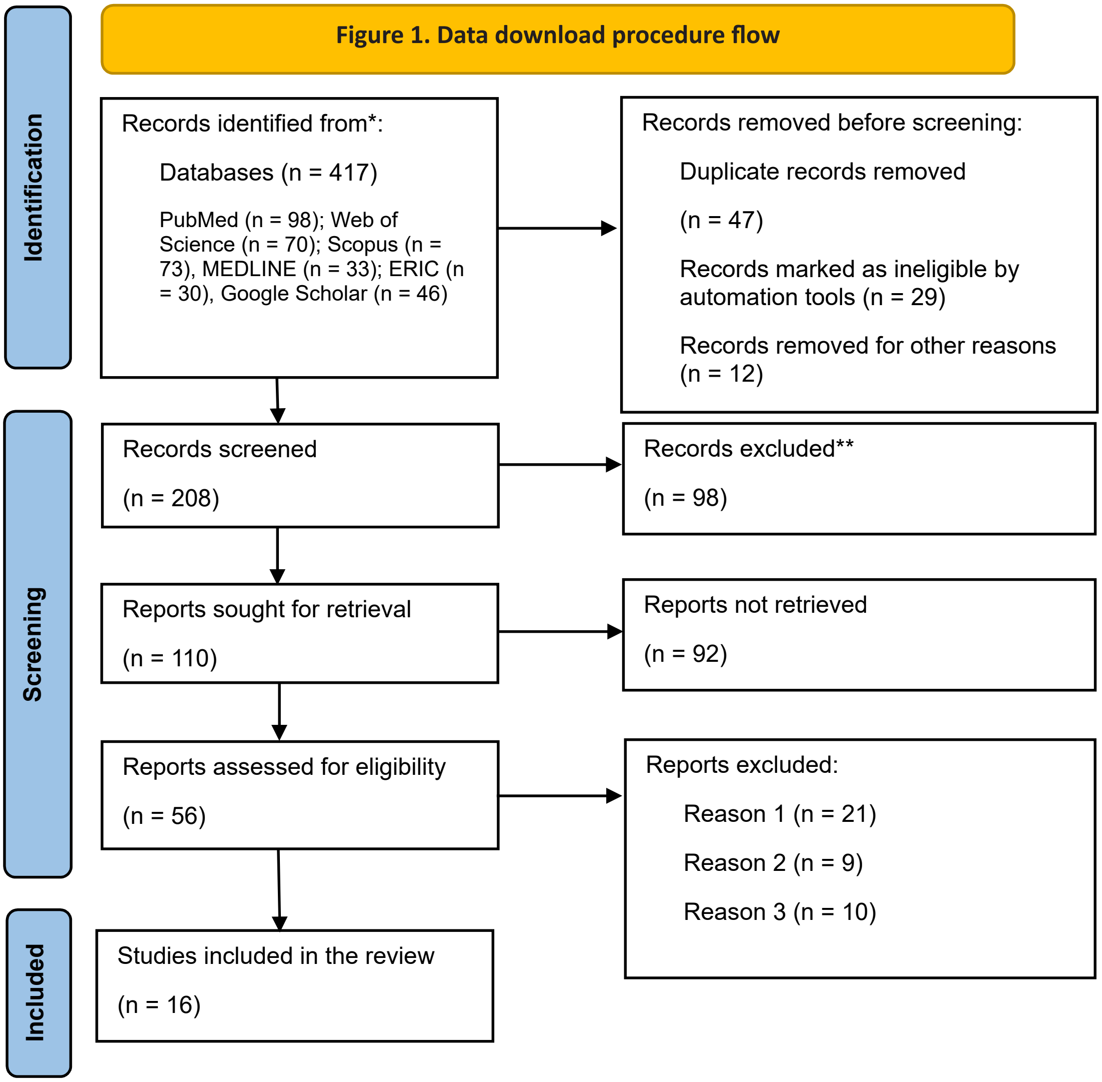

Figure 1. *PRISMA flow diagram, process for collecting studies for systematic review*

Study characteristics

A total of 16 studies investigating the use of artificial intelligence (AI) in the context of physical activity and health were analyzed, with a total of 85,321 respondents. The smallest number of participants was recorded in the study by Jörke et al. (2024), with only 16 participants, while the largest number of participants was included in the study by Chiam et al. (2024), which included 84,764 people. The number of respondents was not emphasized in the works (Chen & Yang, 2020; Choi et al., 2025; Delgoshaei et al., 2025; Kim et al., 2023). The AI methods used are diverse and include conversational agents (PlanFitting – Shin et al., 2023; GPTCoach – Jörke et al., 2024), interactive systems based on LLM and wearable devices (PhysioLLM – Fang et al., 2024), AI for posture correction through video analysis (Pose Trainer – Chen & Yang, 2020; HALE – Lee et al., 2023), as well as systems for personalized health and physical activity (BalanceUP chatbot – Ulrich et al., 2024; AI voice assistants – Hassoon et al., 2021). Deep learning methods have also been used, such as CNN-LSTM for functional movements (Pathak et al., 2022), as well as MediaPipe for shape recognition (Kim et al., 2023).

Table 2. A systematic review of the papers included in the research

Author(s)	Year	Population / Sample	AI / Application	Key findings	AI training performance	Limitations
Shin et al.	2023	18 participants	PlanFitting (conversational AI for workout planning)	It allows users to create and customize weekly exercise plans through natural language, taking into account personal circumstances and goals.	↑	Small sample size; focus on one type of exercise
Chiam et al.	2024	84,764 participants	AI platform for digital health promotion	Increase daily physical activity by 6.17% and weekly moderate to intense activity by 7.61% through personalized daily incentives.	↑	The need for data sharing between clubs for more efficient analysis
Fang et al.	2024	24 Fitbit users	PhysioLLM (interactive health data analysis system)	Integrating physiological data from wearable devices to provide personalized insights and goals, focusing on improving sleep quality.	≠	Small sample size; focus on sleep quality
Chen & Yang	2020	/	Pose Trainer (posture correction app)	Detects user posture during exercise and provides personalized recommendations to improve form and reduce the risk of injury.	↑	Limited to four exercise types; requires a computer with a GPU
Lee et al.	2023	20 women	Home Alone Exercise (HALE)	An application that uses AI to analyze videos of users exercising and provide feedback for posture correction.	↑	Small sample size; focus on one type of exercise
Zhu et al.	2021	53 users	Physical activity app with AI personalization	Using AI to personalize social comparison goals, which can increase users' motivation and physical activity.	↑	Further research is needed to confirm the findings
Jörke et al.	2024	16 participants	GPTCoach (chatbot coach)	Uses motivational interviewing and a personalized approach to encourage physical activity	↑	Small sample size; short-term intervention
Choi et al.	2025	/	LLMOps-based system	Automated exercise analysis and personalized recommendations for users in social healthcare	≠	No empirical data on effectiveness
Ulrich et al.	2024	198 participants	BalanceUP chatbot	Improving mental well-being and reducing somatic symptoms in people with frequent headaches	≠	Specific target group; self-assessment
Kim & Park	2024	51 participants	Mobile app for coaching (with nurse support)	Improving a healthy lifestyle and body composition	↑	Limited to a specific clinical population
Hassoon et al.	2021	42 participants	AI voice assistant and AI text coach	Increase in step count and physical activity compared to the control group	↑	A small sample; short follow-up period
Delgoshaei et al.	2025	/	AI systems for inclusion in physical activities	AI can facilitate the inclusion of people with disabilities in physical activities through personalization and real-time assistance	≠	Lack of empirical data

Jaiswal et al.	2023	60 students	Virtual AI tutor for fine motor skills	Significant improvement in accuracy and speed in learning fine motor skills (e.g. writing) using AI assistants	↑	Experimental setting, short intervention time
Kim et al.	2023	/	Learnable Physics AI for form correction	The AI system uses MediaPipe to recognize movements and provides real-time correction tips, reducing the risk of injury	↑	Limited to simulated conditions; further validation required
Pathak et al.	2022	40 participants	CNN-LSTM system for FMS tests	Automatic assessment of functional movements using AI, with high accuracy compared to physiotherapists	↑	Limited number of moves; limited generalization
Ma et al.	2024	35 athletes	AI fatigue management system (IMU + ML)	Real-time AI-powered endurance and fatigue tracking during training, with the ability to adjust load	↑	Smaller sample size; specificity for the sports population

Legend: *AI – artificial intelligence; CNN – Convolutional Neural Network; LSTM – Long Short-Term Memory; FMS – Functional Movement Screen; IMU – Inertial Measurement Unit; ML – Machine Learning; ↑ - positive effects of using the AI training system; ≠ - lack of data to evaluate the quality of the AI training system.*

Methodological assessment of the quality of the included studies

The methodological quality of the included studies was assessed using the PEDro scale (Physiotherapy Evidence Database). Of the sixteen (n = 16) studies, four were rated as moderate quality, while the remaining studies were classified as low methodological quality, mainly due to the lack of randomization, blinding, and empirical data. The analysis was conducted in accordance with the PRISMA guidelines. Both longitudinal and cross-sectional studies addressing the effects of applying artificial intelligence (AI) in training and planning physical activity were included.

Table 3.PEDro *scale for assessing methodological relevance and quality of studies*

Reference	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Shin et al. (2023)	+	-	-	-	-	-	-	-	-	+	+	**3**
Chiam et al. (2024)	+	+	-	+	-	-	-	+	-	+	+	6
Fang et al. (2024)	+	-	-	-	-	-	-	-	-	+	+	**3**
Chen & Yang (2020)	+	-	-	-	-	-	-	-	-	+	+	**3**
Lee et al. (2023)	+	-	-	-	-	-	-	-	-	+	+	**3**
Zhu et al. (2021)	+	+	-	+	-	-	-	-	-	+	+	**5**
Jörke et al. (2024)	+	-	-	-	-	-	-	-	-	+	+	**3**
Choi et al. (2025)	+	-	-	-	-	-	-	-	-	-	+	**2**
Ulrich et al. (2024)	+	-	-	-	-	-	-	-	-	+	+	**3**
Kim & Park (2024)	+	+	-	+	-	-	-	-	-	+	+	**5**
Hassoon et al. (2021)	+	-	-	+	-	-	-	-	-	+	+	**4**
Delgoshaei et al. (2025)	+	-	-	-	-	-	-	-	-	-	+	**2**
Jaiswal et al. (2023)	+	+	-	+	-	-	-	-	-	+	+	**5**
Kim et al. (2023)	+	-	-	-	-	-	-	-	-	+	+	**3**
Pathak et al. (2022)	+	+	-	+	-	-	-	-	-	+	+	**5**
Ma et al. (2024)	+	+	-	+	-	-	-	-	-	+	+	**5**

Legend:*+ indicates one point; - indicates no point; (1) Eligibility criteria; (2) Radomization; (3) Concealment of allocation; (4) Between-group homogeneity; (5) Blinded of subjects; (6) Blinded trainers; (7) Blinded testers; (8) Dropout rate < 15%; (9) Intention-to-treat; (10) Statistical be-tween-group comparisons; (11) Point and variability estimates; (12) total scores.*

Discussion

The application of artificial intelligence (AI) in sports training brings numerous benefits that can improve athlete performance. The results presented in this systematic review indicate that AI is increasingly integrated into various aspects of sports, from biomechanical analysis of movements, through load planning, to performance prediction and injury prevention. One of the most important findings from the included studies is the ability of AI systems to analyze large amounts of data in real time and provide feedback that is specific, personalized and immediately applicable. According to research conducted by Connolly et al. (2021), the use of machine learning to assess biomechanical parameters during running allowed for timely correction of technique, which resulted in a reduction in the risk of injury.

The work of Lamas, et al. (2022) highlights that the application of AI learning can predict athlete fatigue by analyzing movement patterns and physiological signals. This can help coaches optimally adjust loads to prevent overtraining. However, an important challenge is the need for high-quality and reliable data, as well as ethical standards regarding athlete privacy. Despite the obvious advantages, most of the included studies show limited applicability in real-world training conditions. Many studies (Taylor et al., 2020; Li et al., 2021) were experimental in nature and conducted in controlled conditions, which makes it difficult to generalize the results. Additional research is needed to test the effectiveness of AI systems in long-term and complex sports environments.

PEDro's analysis of study quality indicates variable methodological quality of research, with only some meeting the criteria. This further highlights the need for standardization of methods for evaluating AI systems in sport.

Recent studies have explored the effects of AI-based technologies on motor fitness and physical education. AI-generated calisthenics training programs have shown improvements in flexibility and muscular endurance, although human-made programs were superior in some areas (Masagca, 2024). AI-guided assistance systems integrating motor learning principles, machine learning algorithms, and sensor technologies offer potential for motor skill training in real-world environments (Vandevoorde et al., 2022). Chatbot-generated personalized fitness regimens have demonstrated promise in strength and conditioning applications, although further research is needed (Bays et al., 2024). In college physical education, AI applications such as Intelligent Computer-Aided Instruction, wearable devices, and motion capture systems have enhanced precision and efficacy (Mao & Chen, 2024). AI algorithms have shown superior performance in identifying sports movement features and human body detection compared to traditional methods, reducing errors by 36.69% (Mao & Chen, 2024). These findings suggest AI's potential to revolutionize motor fitness training and physical education.

The application of artificial intelligence (AI) in modern sports training shows the potential to transform the way in which the development of motor skills and the optimization of physical preparation are approached. The most effective AI trainings are based on a combination of personalization, real-time feedback and analysis of large amounts of data, which allows a high level of precision in determining the load, technique and progression. Chatbot assistants such as FitBot, based on NLP models, have shown the ability to generate programs for the development of strength and endurance that are comparable to those created by experts, especially in the context of recreational training (Bays et al., 2024). AI systems that include machine learning and wearable devices enable biomechanical analysis of movements, which accurately detect technical errors and potential risks of injury (Connolly et al., 2021).

In terms of intensity, most AI-guided workouts favor medium to high loads (60–85% 1RM), especially in the development of muscle strength and hypertrophy. At the same time, flexibility, coordination, and endurance are developed through AI routines that use higher repetitions and carefully controlled movements at lower intensities (Masagca, 2024). The integration of sensors and movement pattern recognition algorithms allows for continuous performance monitoring, while reinforcement learning models learn from feedback and adapt training according to changes in the athlete's physiological response (Lamas et al., 2022).

Vandevoorde, et al. (2022) point out that AI-assisted systems that incorporate motor learning principles can effectively improve technique in real-world sports environments, which is of particular importance for the development of coordination and agility. Also, studies in the context of physical education at universities show that the application of AI systems such as wearable devices, ICAT (Intelligent Computer-Aided Training), and movement tracking systems significantly increase the accuracy of performance and motivation of students (Mao & Chen, 2024). It is especially important to emphasize that AI can be an effective tool for personalizing training based on physiological and biomechanical parameters, thus ensuring optimal progression and prevention of overtraining.

The implementation of AI technology in sport still faces challenges such as ethical issues related to data privacy and the need for standardization of evaluation methods. However, a growing body of evidence suggests that AI will play a key role in the future of sports coaching, with the potential to enhance motor skill development through a high level of personalization and adaptation.

Study limitations

The systematic review provides significant insights into the potential of AI applications in the field of training, however, a number of limitations have also been identified. First, most of the included studies have a small number of participants, which limits statistical power and the possibility of generalizing the results. Second, the application of AI technologies has in many cases been tested in controlled conditions, rather than in real training situations, which calls into question their validity. Third, a large number of studies were assessed as having low methodological quality according to the PEDro scale, with a lack of randomization and blinding methods. Another issue is the pronounced heterogeneity of the AI systems, interventions and measurement instruments used, which makes it difficult to compare results across studies.

Conclusion

Based on the results of the systematic review, it can be concluded that artificial intelligence has significant potential for improving motor skills in physical exercise and sports training. AI systems enable personalization of training, precise biomechanical analysis of movements, automated technique correction and improved user motivation. Analysis of the included studies indicates that the most effective programs lasted between 5 and 8 weeks, with a frequency of at least three training sessions per week, while more significant effects were recorded in experimental programs that included personalized feedback and adaptive algorithms. However, current research is still not sufficiently uniform or methodologically precise to draw definitive conclusions about the long-term effect of these technologies. Further empirical research with larger samples and realistic protocols is needed to confirm the effectiveness of AI systems and enable their wider application in sports and physical education.

Conflict Of Interest
No potential conflict of interest relevant to this article was re-reported.

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