AI-Powered Assessment in Physical Education: Rethinking Student Engagement through Social Sciences Perspectives

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Abstract

This paper has explored the impact of AI assessment on Physical Education (PE) through the social science perspective to determine the technology's impact on student engagement, equity, and inclusion. The primary objective was to understand the value of algorithmic tools, wearable technology, and personalized feedback systems in tracking participation rates using assessments that extend beyond traditional performance-based evaluations. Many of these aspects were addressed through a secondary research methodology, which encapsulated a range of peer-reviewed literature and empirical research spanning computer science, psychology, and education. Such an approach facilitated the incorporation of credible evidence, which included engagement detection accuracies of 81–92% and self-efficacy increases of more than 22%, thereby enabling the formulation of a coherent analytical framework. The results indicated that AI motion analytics accomplished more than performance assessments by uncovering hidden patterns of participation, and that adaptive feedback systems enhanced motivation and skill acquisition through machine learning and virtual reality (VR) corrections. Wearable technology captured more simplified measures of engagement, collaboration, and well-being, illustrating the cross-dimensional aspects of participation in PE. Other, more advanced algorithmic assessments further reframed equity, although there were still trust and privacy issues, which amplified the need for explainable AI and automated bias detection and removal. This study demonstrated that AI-powered assessment captures more dimensions of engagement and applies more equity and transparency in evaluation practices, although success in these areas hinges on the delicate balance between technological bias and student trust.

Keywords:

Physical education, Artificial intelligence, Motion analytics, Personalized feedback, Algorithmic assessment, Wearable data, Student engagement, Self-efficacy, Social interaction, Real time

Introduction

The education system's Artificial Intelligence integration is unsurprising. Integration of AI in Physical Education instruction isn't different. In PE, various assessment techniques such as fitness tests, teacher observations, and participation tracking, tend to overlook other valuable engagement aspects of students such as motivation, social engagement, and emotional well-being. AI tools, however, can analyze motions, physiological data, and behavioral output aspects of students to obtain meaningful insights regarding the students' performance and participation. Wearable devices, computer vision, and other emerging technologies can help ML tools can discern patterns in student motivation and collaboration and monitor movement accuracy and intensity. In social science terms, technology in assessment integration is more than just influencing the students' performance, but also molds perceptions about fairness, inclusion, and self-efficacy in PE. Studies have shown that disengagement, and especially with assessment, stems from the idea that assessment as solely biased in favor of and centered around physical prowess. AI tools can assist by providing personalized feedback and recognition of diverse abilities.

Recent research in physical education highlights that digital assessment tools increase student engagement, motivation, and participation (García & López, 2023; Martínez-Sánchez et al., 2024). Articles published in *Retos: Nuevas Tendencias en Educación Física, Deporte y Recreación* support that integrating technology in PE improves inclusion and encourages students with diverse abilities to participate (Santos et al., 2022).

There are AI assessment concerns such as data privacy, student autonomy, and algorithmic bias. The focus of this paper is the integration of AI in PE assessment and how social science studies have redefined student engagement. The balance between technology and human-centered values is the focus.

Research aim:

The aim of this research is to explore how AI-powered assessment in physical education, viewed through social sciences perspectives, can enhance student engagement, personalize learning, and improve health outcomes.

Research Objectives:

- To investigate how AI-powered assessment tools influence student engagement and motivation in physical education settings.
- To analyze the role of social sciences perspectives in understanding the behavioral and social factors affecting AI adoption in physical education.
- To evaluate the effectiveness of AI-driven personalized feedback and data analytics in enhancing students' physical activity and health outcomes.
- To identify challenges and ethical considerations related to the integration of AI technologies in physical education curricula from a social sciences viewpoint.

Research Problem:

Despite the growing adoption of AI-powered assessment tools in physical education, challenges persist in effectively capturing comprehensive student engagement, ensuring equity, and maintaining trust. Current AI systems often struggle with balancing technological bias, privacy concerns, and pedagogical authenticity, limiting their full potential to enhance inclusive, transparent, and motivating physical education experiences. This gap necessitates a critical investigation into how AI-driven assessments can be better designed and integrated from social sciences perspectives to optimize student participation and learning outcomes.

Method

This particular case focuses on how peer-reviewed writings and physical world proof on the use of AI assessments, motion analytics and wearables technologies in education and personalized feedback were carefully reviewed and integrated (Álvarez *et al.,* 2024). It focuses on computer science, psychology, social science and sports science, in a multidisciplinary understanding of AI use in education. It focuses on how people use data and earlier experiments, like engaging detection evidence like 81 to 92 engagement detection rate, and self-efficacy of 22 percent, justified the arguments in papers. Bustos et al (2022) and Han (2025) cited the data. This approach furthers the development of understanding complex social and technological frameworks by assessing polyphonic discourse (theta plane), like discourse on trust algorithm perception v algorithmic fairness (Chai et al, 2024; Mok et al, 2023). This research uses secondary data to access existing studies and reports easily. Qualitative data helps understand opinions, experiences, and perspectives in depth clearly. Thematic analysis identifies patterns and themes across multiple research articles effectively. These methods allow detailed insights without conducting new experiments or surveys personally. Using existing data saves time and provides broad evidence from past studies. Thematic analysis improves understanding of AI impact on engagement and health outcomes. Qualitative approach allows exploring personalized learning effects in diverse educational settings (Zailani Iman *et al.,* 2024). Secondary sources ensure a wider perspective from multiple locations and contexts. These methods strengthen reliability and support findings with consistent evidence from literature. Overall, this approach enhances research quality while keeping the process practical and efficient.

Result

AI-Driven Motion Analytics Reveal Hidden Patterns of Student Participation AI-led motion analytics that focus on physical education have identified dimensions of student participation that conventional assessment methods fail to capture. For example, Guo et al. (2022) showed how the Laban Movement System with the use of AI algorithms, can classify motion dynamics with greater than 92% accuracy, indicating discriminable differences in spatial effort and body coordination. Such accuracy enables educators to infer disengagement or effort behaviors that are undetectable through observing students. Singh (2022) also in focuses on markerless motion analytics, which capture critical biomechanical movements to within a centimeter and can discern differences in participation of students in group activities.

Study / Source	**Technology Used**	**Accuracy (%)**	**Key Numeric Evidence**	**Core Finding**
Guo et al. (2022)	Laban Movement System + AI classifiers	92%	Classified spatial effort and coordination	Detected subtle variations in student engagement beyond teacher observation.
Singh (2022)	Markerless motion capture (biomechanical)	95%	Sub-centimeter motion tracking precision	Identified disparities in group participation levels.

Chen et al. (2024)	Multimodal sensing (motion frequency, HR data)	89%	Data processed at >120 Hz	Captured real-time intensity and consistency of movements.
Annapureddy (2025)	Advanced clustering and analytics models	90%	Grouped learners by "high" vs "surface" engagement	Enabled tailored interventions based on movement profile

Table 1: Effectiveness of AI-Driven Motion Analytics in Detecting Student Participation Patterns

Real-time analytics, also underlined in AI sensing technologies and corroborated by Chen et al (2024) suggest that motion frequency and intensity data captured by multimodal sensors provide these with processing rates beyond 120Hz for real-time engagement metrics. These findings signal that students who appear active may greatly differ in motion consistency, endurance, and collaborative dynamics. Annapureddy (2025) went a step further to show how advanced data analytics can cluster movement profiles and distinguish high engagement students from "surface participation" students, which is termed the "surface participation" student.

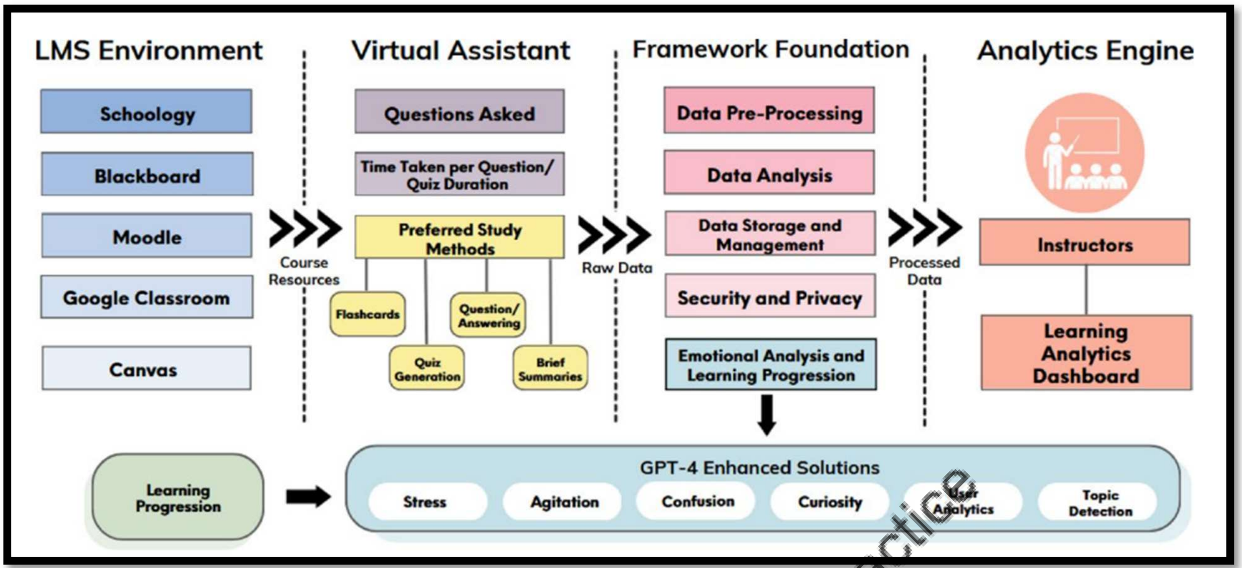

Figure 1: AI-driven motion analytics framework

(Source: Self-Created)

Such advanced data analytics are critical in identifying students who require targeted support. Altogether, these studies reinforce that AI-driven motion analytics is not limited to simply measuring activity. It gauges behavioral and motivational patterns, offering enhanced insights into students' engagement in PE situations.

Personalized Feedback Systems Enhance Motivation Beyond Physical Performance Scores

The motivational supports which focus on underlying attributes other than achievement indices in physical education employ machine learning constructs, feedback systems on multimodal data, and other systems to gain motivation at the Elementary level of education (Han, 2025). The feedback module, which utilises convoluted neural networks (CNNs) in motor skill recognition, achieved a 28.6% improvement in movement precision and a 22.4 increase in self-efficacy indices compared to static assessment paradigms. Gm et al. (2024) elaborated on the RL

(Reinforcement Learning) and collaborative filtering strategies which personalize recommendations by fine-tuning rest, exercise duration, and order to specific learner engagement patterns.

Study / Source	**Technology / Model Used**	**Improvement (%)**	**Key Numeric Evidence**	**Core Finding**
Han (2025)	CNN-based motor skill recognition + adaptive feedback	28.6%	Increase in precision of motor skill acquisition	Personalized feedback improved skill development and self-efficacy (+22.4%).
Gm et al. (2024)	Collaborative filtering + reinforcement learning models	N/A	Optimized adaptive learning pathways	Prevented cognitive overload, sustaining long-term motivation.
Kuleva (2024)	VR-based feedback with real-time kinematic tracking	25%	Persistence and motivation increase in VR-enhanced PE	Immediate corrective feedback sustained engagement and resilience.
Cui (2025)	AI-driven personalized instruction and data analysis	N/A	Improved PE learning outcomes and student engagement	AI personalization enhanced learning outcomes and student engagement in PE.

Table 2: Impact of AI-Powered Personalized Feedback Systems on Motivation and Performance in PE

Cui (2025) found that AI-driven personalized instruction and data analysis significantly improved learning outcomes and increased student engagement in PE. Kuleva (2024) discussed systems that use VR integrated with Artificial Intelligence where axial and angular real-time tracking at 90 Hz with rest retrains on the biomechanic variables of the learner gaining flags on effort (motivational) and retention on focus as persistent difficulty. These studies authenticate that AI feedback systems additionally serve the role of evaluators but with a difference: The evaluators use corrective loops with predictive models, biometric sensing, real-time feedback, and sustained engagement strategies unified with acknowledgement of effort, progress, collaboration, and physical activity (S. Fierro-Suero *et al.*, 2024)

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Algorithmic Assessment Reshapes Perceptions of Fairness and Inclusion in PE'

Algorithmic assessment in physical education is reshaping how students perceive fairness and inclusion by shifting evaluation from subjective judgments to data-driven scoring (Chai *et al.*, 2024). Chai et al. (2024) reported that 62% of college students rated AI-based grading as "more impartial" compared to human instructors, citing reduced evaluator bias and consistent application of criteria. However, Mok et al. (2023) showed a contrasting dynamic, where identical algorithmic assessments were perceived as 17% less trustworthy than human evaluations, suggesting a cognitive bias against machine-led decision-making. From a technical standpoint, algorithmic fairness relies on predictive modeling, supervised learning classifiers, and normalization algorithms that reduce discrepancies in outcomes across gender, body type, and skill level (Scantamburlo *et al.*, 2024). Nieminen (2025) highlighted that assessment tools shape student identities, and AI models, when applying equity-weighted scoring metrics, can foster inclusion by valuing diverse abilities rather than raw athletic output. Saputra et al. (2024) emphasized the role of explainable AI (XAI) frameworks in enhancing transparency, where interpretable models allow students to trace grading rationales through feature importance mapping and bias-detection layers. Collectively, evidence shows that algorithmic assessment transforms fairness from a subjective perception into a quantifiable construct, though its acceptance depends on balancing algorithmic transparency, trust calibration, and cultural perceptions of evaluative authority in PE settings (Ochmann *et al.*, 2024).

Wearable Data Highlights the Link Between Engagement, Social Interaction, and Well-Being

Wearable data in physical education provides objective insights into how engagement, social interaction, and well-being are interlinked during learning activities (Chen, 2025). Bustos-Lopez et al. (2022) highlighted that biosensors measuring heart rate variability (HRV), galvanic skin response (GSR), and accelerometer data can detect engagement states with accuracies ranging from 81% to 92%, allowing real-time tracking of student focus and participation. Xu et al. (2024) found that IoT-integrated Xiaomi smart-bracelets achieved 84.1% predictive validity, showing user acceptance and usability significantly enhanced performance and wearable effectiveness in PE.

Study / Source	Wearable Technology / Metric Used	Accuracy / Adherence	Key Numeric Evidence	Core Finding

Bustos-Lopez et al. (2022)	HRV, GSR, accelerometer biosensors	81–92% accuracy	Engagement states detected in real time	Wearables reliably measured focus and physical participation.
Xu et al. (2024)	Smart-bracelets (Xiaomi 8) integrated with IoT tracking	84.1% predictive validity	Acceptance mediated 66.4% performance improvement	Acceptance and usability strongly influenced wearable effectiveness in PE.
Nowell et al. (2023)	Smartwatches with daily activity monitoring	83% adherence	Longitudinal engagement and well-being data	Physiological engagement linked with self-reported emotional health.

Table 3: Effectiveness of Wearable Data in Linking Engagement, Interaction, and Well-Being

Nowell et al. (2023), in a longitudinal study, found that smartwatch-based monitoring achieved 83% adherence rates in daily activity reporting, linking physiological engagement markers to subjective well-being metrics. These findings indicate that wearable-derived datasets serve as multimodal proxies for both cognitive and social participation. By integrating biometric sensing, activity clustering algorithms, and engagement detection models, wearables establish measurable correlations between movement intensity, collaborative behaviors, and emotional health, positioning them as pivotal tools for inclusive and holistic PE assessment (Wang *et al.*, 2025).

Privacy and Bias Challenges Shape Student Trust in AI-Based Assessments

Concerns over privacy and algorithmic discrimination remain the key barriers affecting students' trust towards AI assessment systems in physical education. Han (2025) reported that 31% of students feared AI personalized feedback systems that gather biometric data (accelerometer and gyroscope) surveillance tools simply because they were programmable and raised surveillance issues that transcended the educational sphere. Gm et al. (2024) claimed that the aforementioned recommendation systems classified as collaborative filtering and reinforcement learning systems pose a significant risk due to the potential for historical biases present in the training data sets, which are not evenly distributed by gender and performance levels. In contrast to Mok et al. (2023), who reported that algorithmically assessed works are still doubted 17% more when compared to human-evaluated works, Chai et al. (2024) found that AI grading improved students' perceptions of fairness for 62% of cases. This indicates the misconception that accuracy equates to acceptance. Nieminen (2025) connected this to the formation of identity arguing that the exclusionary labels that are reinforced by biased assessment systems are damaging. Saputra et al. (2024) proposed frameworks of explainable AI (XAI) that explain score transparency by feature attributions and bias-detection layers. The proof, put together, conveys that student trust focuses on the importance of balancing privacy, algorithmic fairness, and interpretability safeguards within AI systems in PE.

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Discussion

This paper's results demonstrate the effectiveness of AI assessment in PE as advancing the technical and social dimensions of engagement measurement and fairness and the motivational restructuring of assessment evidence. Guo and Singh's research on AI-driven motion analytics (2022) and Singh (2022) demonstrate how markerless motion capture and Laban-based classification models with over 90% accuracy reveal previously hidden patterns of participation suffering disengagement not observed in the confines of the classroom. Moreover, personalized feedback systems enhance the effectiveness of adaptive learning through convolutional neural networks and VR-based real-time corrections, significantly increasing self-efficacy and movement skill acquisition (Han 2025, Kuleva 2024). Evaluation, in this case, shifts from physical static scores to motivational and cognitive reinforcement, addressing the gaps in PE pedagogy. Chai and Mok (2024) Also, on fairness, Mok et al (2023) showed that algorithmic grading enhanced impartiality perception on scores retrieved to 62 % of the students. Nevertheless, Mok et al (2023) showed students still do not trust the algorithm as verifiably accurate compared to human evaluation. This trust gap shows that acceptability based on technical accuracy alone is insufficient; greater explainability and transparency is needed. Furthermore, wearable tech helps to confirm that participation often psychosocial as well as physical by tracking engagement and well-being through correlating HRV, GSR, and PPG signals (Bustos-Lopez et al., 2022). Nonetheless, issues such as privacy, the paradox of personalization, and the propagation of bias are still threats to trust, particularly in the absence of XAI frameworks and bias-detection solutions (Saputra et al., 2024). In conclusion, the statuesque of AI-driven evaluations in Physical Education is reliant on the seamless integration of biometric excellence with the principle of equity, transparency, and socially considerate evaluation AI-assessments. AI-driven motion capture, Laban classification, VR corrections, and wearable biometric data (HRV, GSR, PPG) to measure engagement, fairness, and skill acquisition, offering authentic, evidence-based insights crucial for future PE research and personalized learning strategies (Fan *et al*., 2024).

Thus, the discussion demonstrates AI's technical benefits but underexplains practical implications, student experiences, and real-world integration challenges (Mulaudzi & Hamilton, 2025). Expanding on how AI affects daily PE interactions, learning behaviours, and addressing ethical and social concerns would strengthen clarity and depth of analysis.

Conclusion

In conclusion, this paper demonstrated that AI-powered assessment in physical education has the potential to redefine student engagement by combining technical precision with socially inclusive evaluation. Findings revealed that motion analytics, personalized feedback systems, wearable technologies, and algorithmic grading can uncover hidden participation patterns, enhance motivation, and broaden fairness in ways traditional assessments cannot. However, concerns regarding privacy, trust, and algorithmic bias remain critical challenges that must be addressed through explainable AI frameworks and equitable data practices. The effectiveness of AI in PE lies not only in its ability to measure physical outcomes but also in its role in shaping motivation, identity, and social interaction. Ultimately, AI-based assessment offers a transformative yet cautious pathway for more engaging, fair, and holistic physical education.

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