



Biomechanical Analysis Technologies in Physical Education: A Systematic Review of Motion Analysis, Markerless AI, and Virtual Laboratories

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ABSTRACT

The rapid digitalization of education and the ongoing decline in youth physical activity have increased pressure for physical education (PE) to shift from observation-based instruction to analytically grounded, responsive teaching methods. Biomechanical analysis technologies facilitate this shift by making movement visible, measurable, and understandable for teachers and students. This review synthesizes recent research on how these technologies are being used to innovate PE, focusing on low-cost video analysis, AI markerless pose estimation, and virtual labs. A systematic review of peer-reviewed studies published between 2017 and 2025 was conducted, using keywords related to biomechanics, PE, Kinovea, Dartfish, pose estimation, AI, and virtual labs, sourced from Google Scholar, ScienceDirect, and PubMed. After screening titles, abstracts, and full texts against established criteria, 53 studies were included in the primary analysis; recent publications from 2026 were also included to investigate emerging implications. The review found that affordable motion analysis tools like Kinovea and Dartfish support formative feedback and reflective learning; AI-based markerless systems such as OpenPose, MediaPipe, MoveNet, and RTMPose enhance accessibility to quantitative movement assessment; and virtual labs improve conceptual understanding, learner independence, and blended learning. However, measurement accuracy issues, infrastructure disparities, data governance concerns, and limited teacher expertise in digital biomechanics continue to limit adoption. The unique contribution of this article is its integration of biomechanics, AI, and digital pedagogy into a comprehensive educational framework, rather than treating them as separate technical trends. The review concludes that biomechanical analysis technologies can significantly boost motor learning, assessment quality, and curriculum relevance when combined with teacher training, pedagogically sound implementation, and equitable institutional support. These findings offer a practical roadmap for modernizing PE into an inclusive, evidence-based, and forward-looking field.

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I. INTRODUCTION

Physical education (PE) remains one of the few school subjects that simultaneously develops motor skills, health literacy, social interaction, and habits important for lifelong wellbeing. Current research consistently shows that structured PE and deliberate physical activity enhance fundamental motor skills, coordination, and movement confidence, which are linked to better participation in sports and healthier life paths (Han et al., 2022; Ramos-Campo & Clemente-Suárez, 2024). These connections are particularly significant during childhood and adolescence, when movement quality, enjoyment, and self-view are still highly adaptable. Beyond motor skills, quality PE is associated with broader educational objectives, such as boosting self-esteem, increasing classroom involvement, and fostering sustainable active lifestyles (Allimant et al., 2023; Wibowo, 2024). For this reason, PE should not be viewed as a secondary or recreational subject but as an essential educational domain in which students learn to understand their bodies, control effort, and apply movement knowledge in everyday practice.

At the same time, the context in which PE operates has changed substantially. Sedentary screen-based lifestyles, ubiquitous mobile devices, and the wider digitalization of schooling have altered how students attend to information, how they practice skills, and how teachers assess performance. Recent reviews show that digital-intelligent technologies are rapidly entering PE through wearables, computer vision, data analytics, gamified platforms, and virtual environments, creating new possibilities for individualized feedback and evidence-informed lesson design (Quintero et al., 2024; Zhong et al., 2025). Post-pandemic shifts toward blended and online learning have further expanded interest in technology-mediated PE, while also exposing the limitations of instruction that depends exclusively on live demonstration and teacher observation (Yu & Jee, 2020; Yanto et al., 2022). In this context, innovation in PE is no longer merely about adding digital tools for novelty. Rather, it involves redesigning learning so that students can observe movement more critically, access feedback more quickly, and develop digital competence alongside physical literacy.

Despite these developments, movement analysis in most school-based PE remains largely subjective. Teachers often rely on visual inspection, verbal cues, and endpoint performance measures, even when the learning objective concerns coordination, sequencing, or biomechanical efficiency. Biomechanics offers a scientifically grounded approach to address this limitation by enabling movement to be decomposed into interpretable variables such as joint angles, timing, velocity, alignment, and stability. In sports science and rehabilitation, biomechanical feedback has already been shown to support skill refinement, reduce injury risk, and enable more precise motor assessment (Agresta et al., 2022; Wang et al., 2022). Yet school

uptake remains limited because conventional motion-capture systems are expensive, technically demanding, and poorly matched to ordinary classrooms. The problem, therefore, is not the pedagogical irrelevance of biomechanics but the gap between its educational value and its feasibility in everyday PE settings, especially where infrastructure, teacher expertise, and technical support remain uneven (Helmi et al., 2024; Hernández-Mustieles et al., 2024).

Recent technological developments offer a plausible solution to this gap. First, low-cost video analysis software such as Kinovea and Dartfish has made two-dimensional movement inspection possible with ordinary cameras or smartphones, allowing teachers and students to slow, annotate, and compare performance without a dedicated laboratory (Puig-Diví et al., 2019; Pueo et al., 2020). Second, AI-based markerless pose estimation systems—including OpenPose, MediaPipe, MoveNet, and RTMPose—have expanded access to quantitative kinematic data by detecting body landmarks automatically from video streams (Needham et al., 2021; Edriss, 2025). Third, virtual laboratories and immersive learning environments have emerged as a way to teach biomechanical concepts through simulation, visualization, repetition, and remote participation, thereby complementing physical practice with conceptual exploration (Li & Liang, 2024; Utamayasa & Mardhika, 2024). Together, these developments suggest that biomechanics can be recontextualized from a specialist laboratory science into a practical pedagogical resource.

Even so, the literature remains fragmented. Validation studies on Kinovea, OpenPose, or related systems often emphasize agreement with laboratory standards rather than the ways these tools alter pedagogy or the learner experience (Fernández-González et al., 2020; Ino et al., 2024). Reviews of digital technology in PE map broad trends in wearables, AI, and smart platforms, but typically do not isolate the distinct contribution of biomechanical analysis to motor learning and assessment (Quintero et al., 2024; Zhong et al., 2025). Likewise, the markerless-motion literature is dominated by sport performance and rehabilitation contexts, whereas virtual laboratory studies tend to come from STEM or health education rather than school PE (Edriss, 2025; Zhang et al., 2021). Recent work also cautions that AI adoption in PE may create new burdens when technologies are pedagogically misaligned, ethically opaque, or beyond teachers' practical capacity, producing a paradox in which more technology does not necessarily improve teaching efficiency (Zha et al., 2025; Yang et al., 2026). What is still lacking, therefore, is an integrated synthesis that examines biomechanical technology not only as a measurement solution but also as a curricular and pedagogical innovation for physical education.

Against this background, this article examines the use of biomechanical analysis

technologies in physical education learning innovation by synthesizing research across three interconnected areas: affordable motion analysis tools, AI-driven markerless pose estimation, and virtual laboratories. The review seeks to clarify how these technologies are applied, their pedagogical value, the limitations that hinder their implementation, and strategic directions to promote more equitable adoption. Its novelty lies in integrating technical, pedagogical, and implementation evidence within a single interpretive framework focused on education rather than elite sports or clinical assessment alone. By doing so, the article provides a more coherent conceptual foundation for aligning biomechanics, digital pedagogy, and curriculum reform in ways that are evidence-based, inclusive, and responsive to the realities of contemporary PE.

II. METHODS

This study employed a qualitative descriptive design through a systematic literature review, because the objective was not to estimate pooled effect sizes but to interpret how different technological approaches are shaping innovation in physical education. A qualitative descriptive review is suitable when a field is heterogeneous in methods, outcomes, and settings, and when the research problem requires conceptual integration rather than narrow statistical aggregation. In the present topic, the literature spans biomechanics, sport science, educational technology, rehabilitation, and teacher development; consequently, an integrative review strategy was better suited to identifying recurring pedagogical patterns and unresolved implementation issues than a meta-analysis limited to a single intervention type. The review was therefore designed to combine systematic searching, transparent screening, and thematic synthesis so that the resulting account would be both analytically rigorous and practically useful for educational decision-making.

The search focused on peer-reviewed publications published from 2017 to 2025, the period in which low-cost video analysis, markerless pose estimation, and virtual laboratory systems expanded most visibly in education and human movement research. Three databases were used—Google Scholar, ScienceDirect, and PubMed—to maximize disciplinary coverage across education, biomechanics, and applied health and sports research. Search strings combined the central concepts of the study using Boolean operators, including “biomechanics” AND “physical education,” “Kinovea” OR “Dartfish” AND “motion analysis,” “markerless pose estimation” OR “OpenPose” OR “MediaPipe” OR “MoveNet” OR “RTMPose” AND “education,” and “virtual laboratory” OR “virtual reality” AND “physical education.” Backward citation checking was also used to identify additional relevant articles from the reference lists of recent reviews. The formal review corpus remained bounded at 53 studies

after screening, while a small number of very recent 2026 publications were consulted only to contextualize emergent implications in the discussion and were not counted in the core sample.

Inclusion criteria required that studies be written in English, published in peer-reviewed outlets, and clearly address one or more of the following: the application of motion analysis technology, markerless AI-based human pose estimation, or virtual/immersive laboratory environments in educational, sport, or rehabilitation contexts with implications for teaching and learning. Empirical studies, systematic reviews, methodological evaluations, and design studies were all considered eligible when they generated interpretable evidence relevant to PE innovation. Exclusion criteria removed dissertations, unpublished manuscripts, non-peer-reviewed websites, duplicate records, and articles whose primary focus was unrelated to human movement learning or pedagogical application. Screening proceeded in three stages—title, abstract, and full-text review—to ensure thematic consistency. For each included source, information was extracted on publication year, technological domain, study context, principal findings, pedagogical affordances, and reported limitations. This process allowed the review to move beyond bibliographic listing toward patterned comparison. Table 1 summarizes the stages through which the evidence base was assembled and synthesized.

The analytical procedure followed an iterative thematic synthesis. During data condensation, the extracted findings were coded according to recurring themes, including accessibility, feedback immediacy, measurement validity, teacher readiness, learner autonomy, and infrastructure dependency. During data display, coded evidence was organized into comparative matrices, enabling the three technological domains to be contrasted in terms of instructional value and implementation burden. Verification involved repeated comparisons between primary studies and the broader review literature, so that interpretations were not anchored in isolated findings but in converging tendencies across the corpus. This step was particularly important because the evidence base includes validation studies, quasi-experiments, scoping reviews, and design-oriented reports with different evidentiary strengths. To strengthen trustworthiness, the synthesis explicitly addressed methodological limitations reported by the original authors, such as restricted ecological validity, small sample sizes, or poor generalizability, and incorporated these limitations into the interpretation of the results rather than treating the evidence as uniformly robust.

Because the review used only secondary literature, no human participant ethics approval was required. Nevertheless, methodological transparency was treated as a core quality criterion. The database sources, keyword logic, temporal boundaries, eligibility criteria, and analytical stages were made explicit to enable future researchers to replicate or extend the review. This

transparency is especially important in fast-moving fields such as AI-based motion analysis, where technical updates occur quickly, and educational relevance can be overstated unless evidence is systematically appraised. The resulting method enabled the study to retain the breadth necessary for an emerging interdisciplinary topic while providing a sufficiently disciplined basis for drawing conclusions about current practice, persistent barriers, and future priorities for biomechanics-enhanced physical education.

Table 1. Summary of data collection and analysis procedures

Research stage	Description	Key output
Literature search and identification	Identification of publications from 2017–2025 using keywords related to biomechanics, physical education, motion analysis, AI-based pose estimation, and virtual laboratories.	Initial pool of potentially relevant studies
Screening	Removal of duplicate or clearly irrelevant records through title and abstract review.	Screened records aligned with the review scope
Eligibility assessment	Full-text examination against inclusion and exclusion criteria covering publication type, language, topic relevance, and pedagogical significance.	Fifty-three core studies retained for synthesis
Data extraction and condensation	Coding of study characteristics, technology type, educational context, major findings, pedagogical affordances, and reported limitations.	Comparative evidence matrix
Thematic synthesis and verification	Cross-comparison of coded findings to identify recurring themes across low-cost motion analysis, markerless AI, and virtual laboratories.	Validated thematic structure for interpretation
Conclusion drawing	Integration of thematic findings into conceptual, pedagogical, and implementation implications.	Interpretive framework and recommendations

As indicated in Table 1, the review process was carefully structured to ensure that the synthesis remained transparent and could be reliably reproduced by others. This approach was also aimed at maintaining interpretive depth, allowing for meaningful insights to emerge from the data. The table further illustrates that the review progressed from a broad identification of relevant articles to a more selective process of thematic integration. Instead of merely listing articles, the process focused on synthesizing themes to provide a clearer understanding of the subject matter.

III.RESULTS

3.1 Overview of the evidence base

The 53 studies in the core corpus revealed a rapidly expanding but uneven field. Most were published after 2021, indicating an acceleration driven by advances in computer vision, lower-cost mobile imaging, and broader institutional interest in digital learning. The studies were methodologically heterogeneous: some validated tools against laboratory standards, some examined intervention effects on learning or motor performance, and others evaluated user experience, system design, or broader implementation conditions. Across this diversity, three technological domains recurred consistently—low-cost video analysis, AI-based markerless pose estimation, and virtual laboratories—suggesting that contemporary biomechanics-enhanced PE is developing along convergent but not identical pathways. As summarized in Table 2, each domain offers a distinctive mix of pedagogical affordances and practical constraints. The evidence also showed that the technologies are not mutually exclusive; rather, they occupy different positions on a continuum ranging from accessible classroom feedback to more advanced automated analytics and immersive conceptual learning.

Table 2. Thematic synthesis of biomechanical analysis technologies in physical education

Domain	Representative evidence	Primary pedagogical affordances	Main implementation constraints
Low-cost video analysis	Kinovea, Dartfish; Puig-Diví et al. (2019); Fernández-González et al. (2020); Pueo et al. (2020)	Visual feedback, self- and peer-assessment, slow-motion review, movement decomposition, accessible formative assessment	Two-dimensional limitation, sensitivity to camera setup, operator dependence, commercial licensing cost for some platforms
Markerless AI pose estimation	OpenPose, MediaPipe, MoveNet, RTMPose; Needham et al. (2021); Ino et al. (2024); Zheng et al. (2025)	Automated keypoint detection, personalized quantitative feedback, longitudinal tracking, scalable analytics with ordinary cameras	Occlusion and lighting sensitivity, uneven lower-body accuracy, dataset bias, interpretation burden, data-governance concerns
Virtual laboratories and immersive systems	Virtual labs, VR, simulation-based modules; Zhang et al. (2021); Li and Liang (2024); Viitaharju et al. (2025)	Conceptual visualization, safe repetition, blended access, higher motivation, inquiry and project support	Hardware and bandwidth demands, variable instructional design quality, dependence on facilitation, cannot replace embodied practice

Table 2 summarizes the main patterns from the literature, highlighting common themes across various studies. The tools discussed differ in technical sophistication, ranging from simple to highly advanced. Despite these differences, the instructional logic they share remains quite consistent. Specifically, each technology is most effective when it helps students visualize movement more clearly, receive quicker feedback, and link practice to explicit evidence.

3.2. Application of low-cost motion analysis tools

Low-cost motion analysis tools were the most immediately classroom-ready category in the literature. Studies on Kinovea repeatedly demonstrated that two-dimensional video analysis can produce acceptable agreement with more sophisticated systems for tasks such as gait analysis, jump assessment, angular measurement, and movement timing, provided that camera placement and recording conditions are carefully controlled (Puig-Diví et al., 2019; Fernández-González et al., 2020; Pueo et al., 2020). The significance of these findings for PE lies less in laboratory equivalence than in usability. Because Kinovea is free and can work with ordinary video files, it allows teachers and students to pause, slow down, annotate, and compare movement sequences without specialist hardware. This shifts feedback from purely verbal correction to visual-analytic discussion, which is particularly valuable for complex skills whose quality is difficult for novice learners to perceive in real time.

Evidence on Dartfish suggested a similar pedagogical role, albeit in a more feature-rich ecosystem. The literature indicates that Dartfish supports synchronized multi-angle comparison, annotation, and model-based performance analysis, making it especially useful when instruction requires side-by-side comparison of a learner's performance with an expert template (Matsuzaki et al., 2021; Morante et al., 2023). Across both platforms, the most frequently reported educational benefit was the strengthening of reflective learning. Repeated viewing, self-talk, and video modeling were found to support self-regulated practice, with students using visual evidence to identify error patterns and modify technique more intentionally (Trabelsi et al., 2021). In that sense, the software did not simply document performance; it altered the structure of learning by giving learners an external representation of movement that could be revisited and discussed.

At the same time, the literature also clarified the boundaries of what low-cost two-dimensional analysis can do. Studies comparing 2D and 3D approaches have shown that planar video analysis is most defensible for movements largely confined to a single plane and less reliable for rotational or highly multi-planar actions (Winkler et al., 2024; Skalski et al., 2025). Measurement quality remained sensitive to lighting, camera height, perspective, and operator

skill, meaning that usability does not eliminate the need for methodological discipline. The corpus, therefore, suggests that low-cost software is best understood as a high-access, moderate-fidelity option: well-suited to formative assessment, peer feedback, and concept teaching, but less suited to tasks requiring full three-dimensional reconstruction or automated decision support.

3.3. Utilization of AI-based markerless pose estimation

A second cluster of results concerned AI-based markerless pose estimation, which has developed more rapidly and with greater technical diversity than the low-cost software literature. Studies on OpenPose, MediaPipe, and related frameworks reported that standard video cameras can be used to identify body landmarks and estimate spatiotemporal or kinematic variables with accuracy that is increasingly adequate for many applied settings (Nakano et al., 2020; Needham et al., 2021; Scott et al., 2022). Subsequent studies reinforced this trend by demonstrating promising validity for specific tasks, such as knee-valgus assessment, postural analysis, and gait evaluation, when algorithms are used under appropriate environmental conditions (Ino et al., 2024; Lee et al., 2024; Yang & Park, 2024). The 2025 mini-review by Edriss (2025) further indicated that commercial vision sensors and open-source pose-estimation frameworks are converging into a more practical ecosystem for sports and exercise analysis, especially as two-dimensional-to-three-dimensional pipelines become more feasible.

In educational terms, the most salient finding was the expansion of access to quantitative feedback. Unlike conventional motion capture, markerless systems remove the need for reflective markers, force plates, or dedicated studios. This lowers the threshold for classroom experimentation and enables performance data to be generated from smartphones or simple cameras. Several studies indicated that such systems could support personalized feedback because joint trajectories, segment positions, or posture deviations can be visualized and revisited quickly, making it easier for learners to connect abstract biomechanical principles with their own movement patterns (Pinheiro et al., 2022; Parashar et al., 2023; Zheng et al., 2025). In principle, this creates a more adaptive PE environment in which students do not all receive the same correction at the same time but rather feedback tailored to their movement profiles.

However, the results were also more conditional than sometimes implied in promotional narratives. Markerless systems have repeatedly been shown to be vulnerable to occlusion, low-light conditions, high-speed action, non-frontal camera angles, and dataset bias, all of which can degrade the stability of landmark detection and reduce measurement validity (Vieira et al., 2022; Menychtas et al., 2023). Lower-limb detection and rapid multi-person interactions

remained particularly challenging. The literature thus suggests that AI does not automatically solve the problem of movement analysis; instead, it redistributes it. Some constraints related to hardware and markers are reduced, but new constraints emerge regarding algorithm selection, validation, computational requirements, data interpretation, and the ethical handling of video-based performance records. Accordingly, the educational usefulness of markerless AI depends not only on the sophistication of the algorithm but also on the teacher's ability to interpret outputs and position them meaningfully within instruction.

3.4. Implementation of virtual laboratories

The third major domain involved virtual laboratories and immersive digital environments. Although the virtual-lab literature was less tightly tied to biomechanics measurement than the previous two domains, it was highly relevant to how biomechanical concepts can be learned. Across the corpus, virtual laboratories were used to simulate experiments, visualize otherwise invisible processes, and provide repeatable practice environments that students could access beyond scheduled class time (Abumalloh et al., 2021; Sujono et al., 2023). Meta-analytic and systematic evidence from broader laboratory education showed consistent positive effects on motivation, engagement, and conceptual understanding, while also noting that virtual environments work best when they complement rather than replace embodied practice (Zhang et al., 2021; Li & Liang, 2024).

In studies closer to motor learning and movement education, immersive or interactive virtual environments were associated with better attention, greater willingness to practice, and stronger opportunities for self-paced exploration (Utamayasa & Mardhika, 2024; Velentzas et al., 2024). Virtual reality motor games and simulation environments also demonstrated potential for skill development and repeated corrective practice, particularly when immediate feedback or gamified progression was integrated into the design (Chen, 2020; Xue et al., 2025; Viitaharju et al., 2025). Project-based virtual-laboratory modules have likewise been designed to strengthen autonomy and conceptual transfer, suggesting that the pedagogical value of simulation is highest when digital experimentation is linked to explicit inquiry tasks rather than passive viewing alone (Purwaningsih et al., 2024). For PE, the main implication is that virtual laboratories can serve as conceptual amplifiers: they make movement mechanics, force direction, angle changes, or timing relationships easier to see and manipulate than in live demonstrations alone. This is especially useful when lesson time is short or when the movement under study is too fast or too complex to decode through observation.

Still, the evidence did not support an uncritical replacement of physical practice by virtual

environments. The virtual-lab literature consistently reported dependencies on internet bandwidth, hardware availability, interface quality, and teacher facilitation. Broader implementation reviews of immersive technology in professional education point to the same pattern: hardware costs and instructor readiness remain decisive determinants of success (Lie et al., 2023). Studies also showed that the educational effect of virtual laboratories varies with prior knowledge, task design, and the extent to which activities are embedded in clear pedagogical purposes rather than used as isolated digital events (Manyilizu, 2022; Li & Liang, 2024; Sidik et al., 2022). Thus, the results position virtual laboratories as a powerful adjunct to biomechanics teaching, especially in blended settings, but not as a stand-alone substitute for bodily experience, live demonstration, or contextual teacher guidance.

3.5. Cross-cutting patterns

Across all three domains, several cross-cutting patterns became visible. First, immediate and visual feedback was the most consistent mechanism linking technology to improved learning. Whether through slowed video, automated pose overlays, or simulated environments, students benefited when movement became inspectable rather than ephemeral. Second, accessibility and precision did not always align. The most accessible tools were not necessarily the most accurate, while the most automated systems still required conditions rarely guaranteed in ordinary PE spaces. Third, successful use depended heavily on teacher competence. Studies on virtual laboratories, wearables, and digital technology in education indicated that even promising systems are easily underused when teachers lack confidence in data interpretation, lesson integration, or troubleshooting (Falfushynska et al., 2022; Hernández-Mustieles et al., 2024). Finally, the corpus showed a persistent imbalance between technical validation and pedagogical evaluation. Many studies have demonstrated that technologies can measure movement, but fewer have established how they improve curriculum quality, equity, or learning progression in school PE. This imbalance became an important point for interpretation in the discussion

IV. DISCUSSION

The most important implication of the findings is that biomechanics technology changes the epistemic basis of PE. Traditionally, much PE teaching relies on demonstration, imitation, and teacher judgment. Those practices remain valuable, but the reviewed evidence indicates that contemporary tools increasingly allow movement to be represented as analyzable evidence. This matters because motor learning is not only about repetition; it is also about perception, interpretation, and the learner's capacity to connect bodily sensation with observable

performance cues. When students can watch a slowed-down movement, inspect a change in joint angle, or compare their performance to a model, feedback becomes more explicit and less dependent on fleeting teacher observation (Trabelsi et al., 2021; Stöckel & Grimm, 2021). In that respect, biomechanical analysis technologies support a shift from impressionistic correction toward evidence-based pedagogy. Such a shift is especially relevant in competency-based curricula, where learning quality is judged not merely by participation, but by demonstrated understanding and progressive control of movement.

Yet the results also show that technological availability alone does not produce pedagogical innovation. The central issue is the alignment between a tool's analytic capacity and the educational purpose for which it is used. Low-cost video analysis is well aligned with formative feedback, peer assessment, and movement decomposition because it slows practice enough for discussion. Markerless AI is aligned with more individualized and longitudinal assessments because it can automate keypoint detection and generate richer analytics. Virtual laboratories align with conceptual modeling, pre-laboratory familiarization, and blended learning by extending access beyond class time. Problems arise when this alignment is absent—for example, when sophisticated AI outputs are introduced without a clear instructional function, or when virtual environments are treated as replacements for embodied practice rather than scaffolds for it. The paradox identified in recent PE-AI studies is therefore understandable: technology can hinder efficiency when it increases cognitive or managerial load without clearly improving feedback quality or learning design (Zha et al., 2025; Yang et al., 2026).

Based on the synthesis, this article proposes a pedagogically aligned biomechanics integration framework comprising four interdependent layers. The access layer concerns the material feasibility of capturing movement through smartphones, tablets, simple cameras, or school-owned devices. The analytics layer concerns the validity and interpretability of the movement metrics generated by software or AI systems. The pedagogy layer concerns how those metrics are translated into tasks such as self-assessment, peer dialogue, differentiated correction, reflective journaling, or project-based inquiry. The governance layer concerns teacher training, ethical video management, data privacy, maintenance, and institutional support. A tool becomes educationally meaningful only when all four layers are addressed. This framework helps explain why some relatively simple tools can yield substantial pedagogical value, while technically advanced systems may fail in practice if governance and pedagogy are neglected.

4.1. Balancing accessibility and measurement fidelity

The reviewed literature suggests that the field is currently negotiating a fundamental trade-off between accessibility and measurement fidelity. Kinovea and comparable tools are attractive because they are inexpensive, transparent, and easy to integrate into school routines. Their relative simplicity also supports teacher agency: instructors can see what the software is doing and explain it directly to students. However, their two-dimensional nature limits their use for highly complex actions. Markerless AI systems extend analytic scope, but they introduce a different set of dependencies, including computational demands, algorithmic opacity, and sensitivity to context. The pedagogical question, then, is not whether schools should always adopt the most advanced tool, but whether the selected tool is sufficiently valid for the learning objective at hand. For introductory skill learning, reflection, and peer feedback, moderate-fidelity tools may be entirely appropriate. For advanced assessment, research-based projects, or movement patterns involving multiple planes, higher-fidelity or mixed systems may be justified. A tiered adoption model, rather than an all-or-nothing technology agenda, is therefore more defensible.

Such a tiered approach is also consistent with the economics of educational innovation. Resource-constrained institutions cannot be expected to replicate laboratory ecosystems, but they can often adopt smartphone-based video capture, open-source analytics, or cloud-supported feedback workflows. Recent SWOT analyses of portable markerless systems underline exactly this point: practical value emerges when systems are low-cost, portable, and sufficiently accurate for the intended context, not when they approximate perfect laboratory control (Armitano-Lago et al., 2022; Edriss, 2025). This has important implications for developing-country contexts, including many Indonesian schools, where bandwidth, device availability, and teacher workload are decisive factors. A realistic innovation agenda should therefore prioritize pedagogical usefulness and scalability over technological maximalism.

4.2. Teacher competence, inclusion, and curriculum alignment

The synthesis consistently identified teacher competence as the decisive mediator between technological potential and classroom impact. In a literal sense, biomechanics technology produces data. But data do not teach students on their own. Teachers must decide what variable matters, how to explain it in age-appropriate language, when to use individual rather than group feedback, and how to ensure that digital tools deepen rather than fragment participation. Studies on virtual laboratories, wearables, and digital PE repeatedly show that professional development is most effective when it combines technical operation with pedagogical design,

reflective practice, and subject-specific reasoning (Falfushynska et al., 2022; Hernández-Mustieles et al., 2024). The same conclusion is reinforced by the newest PE-AI literature, which reports that teachers' self-efficacy, perceived usefulness, and institutional environment shape whether AI is adopted meaningfully or resisted as an additional burden (Yang et al., 2026).

Teacher competence also matters for inclusion. Biomechanical technologies can support inclusive PE by enabling individualized pacing, clearer visual cues, and differentiated feedback for students whose movement patterns, prior experience, or confidence differ from the class average. Virtual and visual tools may be particularly helpful for learners who benefit from repeated observation, multimodal explanation, or self-paced rehearsal. At the same time, inclusion cannot be assumed. Algorithmic systems trained on limited datasets may perform unevenly across body types, clothing conditions, or group interactions, while unequal access to devices or connectivity can reproduce existing educational disparities (Vieira et al., 2022; Menychtas et al., 2023). Inclusion, therefore, requires deliberate design choices: low-bandwidth options, shared-device workflows, opt-in video policies, and assessment practices that use analytics to support growth rather than label deficiency.

These findings resonate with the priorities of competence-based and student-centered curricula, including Indonesia's Kurikulum Merdeka. When implemented well, biomechanics technology can support critical observation, communication, collaboration, and self-regulation—competencies that extend beyond immediate motor execution. Students can record a movement, annotate errors, justify corrective strategies, compare iterations, and present evidence of improvement. In other words, the technology can turn PE into a site of inquiry rather than a one-way instructional model. This is pedagogically important because it helps counter the persistent misconception that PE is only about activity volume or performance outcome. Instead, it positions movement as a legitimate object of analysis, explanation, and reflective learning. An especially promising direction is the integration of biomechanics tools with project-based and problem-based learning. Students can investigate questions such as why a jump becomes more stable, how arm swing affects a sprint start, or how balance changes across trials, using video or AI outputs as evidence. Such designs could help bridge the technical aspects of biomechanics with the inquiry-oriented expectations of twenty-first-century curricula.

3.3. Sustainability, ethics, and future research directions

The review also suggests that biomechanical technology is relevant to sustainability and long-term educational modernization. Virtual laboratories and portable video systems can reduce

dependence on specialized facilities, expand access beyond school hours, and enable hybrid learning modes that are less vulnerable to disruption (Abumalloh et al., 2021; Li & Liang, 2024). However, sustainable adoption is not merely a matter of lower cost. It also involves maintenance, interoperability, teacher turnover, data governance, and avoiding short-lived pilot projects. Schools need clear protocols for video storage, consent, reuse, and deletion, particularly when minors are involved or when AI platforms process visual data on external servers. These issues have not been examined as deeply as technical performance, which is a significant weakness in the current literature.

Another notable limitation in the evidence base is the dominance of validation studies and higher-education or sport-performance contexts. While such studies are valuable, they do not automatically tell us how technology works in large, noisy, mixed-ability school classes. Future research should therefore move in three directions. First, more school-based intervention studies are needed to test how biomechanics technologies affect motor learning, motivation, assessment fairness, and teacher workload over time. Second, comparative studies should examine different implementation models, for example, simple video feedback, AI-assisted analytics, and blended virtual-laboratory approaches, so that adoption decisions can be based on educational value rather than mere technical novelty. Third, the field needs stronger frameworks for ethical and pedagogical evaluation, including criteria for interpretability, inclusiveness, and curricular coherence. Without such work, the discourse may remain over-weighted toward capability and underdeveloped in relation to educational quality.

Taken together, the findings support the idea that biomechanics technology is not just a supplementary tool for PE but part of a broader pedagogical shift. It encourages teachers to move from one-time correction to ongoing feedback, from generic instruction to more personalized learning paths, and from implicit judgment to more transparent evidence. However, the review also warns against technological determinism. The most effective future for PE is not about replacing human expertise with algorithms, but about teachers using thoughtfully selected technologies to enhance observation, dialogue, and reflective practice. In that sense, the true innovation is not just the software itself; it's the redesign of PE as a more analytical, inclusive, and future-focused field of education.

V. CONCLUSION

This study demonstrates that biomechanical analysis technologies have shifted from being peripheral research tools to becoming practical drivers of pedagogical change in physical education. Out of the 53 studies reviewed, three areas consistently stood out as influential: low-

cost motion analysis tools, AI-based markerless pose estimation systems, and virtual laboratories. Low-cost software such as Kinovea and Dartfish expand access to visual feedback and reflective assessment; AI systems without markers enhance this capability through automated detection and more personalized quantitative feedback; and virtual laboratories improve conceptual understanding, learner autonomy, and blended learning approaches. Together, these technologies facilitate a shift from subjective observation to evidence-based movement instruction, making motor processes that are usually hard for students to perceive more visible. The review also highlights that pedagogical value does not automatically come from technological complexity. Instead, it relies on the compatibility between the tool, learning goals, classroom context, and teacher expertise. When this alignment is achieved, biomechanics technology can boost assessment quality, student engagement, digital skills, and the relevance of PE in a data-driven educational environment.

Several limitations remain in this study. The current evidence base is dominated by higher-education, sport-performance, and methodological validation studies, while rigorous school-based interventions—especially in primary and secondary education—are still comparatively scarce. The literature also varies widely in outcome measures, making cross-study comparisons difficult, and ethical issues surrounding data security, consent, and algorithmic bias remain underexamined. Future research should therefore test long-term classroom implementation models, compare low-cost and high-automation approaches across diverse settings, and develop evaluation frameworks that integrate measurement validity with pedagogical, ethical, and inclusion criteria. Despite these limitations, the present study contributes an integrative framework that links access, analytics, pedagogy, and governance as essential conditions for successful adoption. This contribution is important because it redefines biomechanics technology not merely as an instrument for measuring movement, but as a means of redesigning physical education into an inclusive, reflective, and future-oriented discipline. For educators, researchers, and policymakers, the implication is clear: investments in biomechanics-enhanced PE should prioritize teacher development and curricular integration as much as hardware and software acquisition.

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