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Utilization of Artificial Intelligence in Analyzing Movement Errors in Physical Education Learning Among PJKR Students

Bahrul Alim
[1] Univeritas Negeri Makassar, Indonesia.
* Coressponding Author. E-mail: bahrul.alim@unm.ac.id

Abstract
Accurate analysis of movement errors is crucial in physical education (PE) instruction for improving student performance and preventing injuries. However, traditional observation methods often involve subjective interpretations and human limitation. This study aimed to investigate the utilization of Artificial Intelligence (AI) in analyzing movement errors during physical education learning among students of Physical Education, Health, and Recreation (PJKR) at the Faculty of Physical Education and Health Sciences (FIKK), Universitas Negeri Makassar (UNM). This research employed a mixed-methods approach involving 120 PJKR students across different academic years. The study utilized computer vision technology with deep learning algorithms to detect and classify movement errors in fundamental sport movements. Data collection involved video recording of students performing three basic motor skills: basketball shooting, badminton forehand stroke, and long jump. The AI system was trained using a dataset of 2,000 movement samples with accurate and erroneous movement classifications. Results indicated that the AI-based system achieved 94.5% accuracy in identifying movement errors compared to expert coaches' assessments. Students receiving AI-assisted feedback demonstrated significant improvement in movement accuracy, with a mean improvement of 32.7% compared to the control group receiving traditional instruction ($p < 0.001$). The implementation of AI technology not only enhanced the precision of error detection but also provided immediate, objective feedback that facilitated faster learning progression. Furthermore, this technology enabled real-time monitoring and personalized learning pathways for individual students. This study demonstrates that AI integration in PE learning settings offers promising potential for enhancing instructional effectiveness, improving student outcomes, and creating more objective assessment systems in physical education.

Keywords: Artificial Intelligence, Movement Analysis, Physical Education, Computer Vision, Deep Learning, Motor Skill Assessment

INTRODUCTION

Physical education plays a fundamental role in fostering healthy lifestyles, developing motor skills, and promoting physical fitness among university students (Kemenpora, 2020). The primary objective of physical education instruction is not only to develop students' physical competence but also to cultivate attitudes and values that support lifelong physical activity engagement (Pratama & Nugraha, 2021). However, the effectiveness of physical education learning depends significantly on the quality of instruction, particularly in the accurate identification and correction of movement errors. Traditional teaching methods in physical education rely heavily on the instructor's subjective observation and verbal feedback, which often cannot capture all aspects of student movement with precision (Sujarwanto et al., 2022).

Movement analysis in physical education is essential for several reasons. First, accurate identification of movement errors prevents students from developing incorrect motor patterns that could lead to plateaus in performance or increase injury risk (Hermawan & Pratama, 2020). Second, timely corrective feedback enhances learning efficiency by allowing students to adjust their movements immediately during practice sessions (Wijaya et al., 2021). Third, objective movement assessment provides equitable evaluation for all students, reducing bias that might occur in subjective teacher assessment (Rahman & Sulistyaningsih, 2022). However, traditional observation methods face significant limitations, particularly in large class sizes where teachers cannot provide individual attention to each student consistently (Nugraha et al., 2020).

Recent advances in technology have introduced innovative solutions to these challenges. Artificial Intelligence, particularly through computer vision and deep learning technologies, offers unprecedented opportunities to revolutionize physical education instruction (Budiman et al., 2023). Computer vision systems can analyze movement in three-dimensional space, capturing subtle biomechanical details that human observation might miss (Putri & Santoso, 2021). Deep learning algorithms, trained on extensive datasets of correct and incorrect movements, can classify movement patterns with remarkable accuracy and consistency (Setiawan et al., 2022). These systems provide immediate, objective feedback to learners, enabling them to correct errors instantaneously and reinforcing correct movement patterns (Wirawan et al., 2023).

The integration of AI in physical education represents a paradigm shift from subjective, reactive instruction to objective, real-time intervention (Sutrisno & Wijaya, 2021). At Universitas Negeri Makassar, the Physical Education, Health, and Recreation (PJKR) program has recognized the importance of incorporating modern technology to enhance instructional quality and student outcomes. The faculty has begun exploring AI applications in movement analysis, recognizing that future PE teachers need to be equipped with contemporary technological skills and understanding. However, empirical research on the effectiveness of AI implementation in the Indonesian physical education context remains limited (Hermawan et al., 2023).

This study addresses this research gap by investigating how AI-based movement analysis can be effectively integrated into PJKR learning environments. Specifically, this research examines the accuracy of AI systems in detecting movement errors, the impact on student learning outcomes, the quality of feedback provided, and student perceptions of AI-assisted learning. Understanding these aspects will provide valuable insights for physical education institutions seeking to enhance their instructional methods and prepare students for technology-integrated PE teaching practices. Furthermore, this research contributes to the growing body of literature on educational technology adoption in Indonesian higher education institutions (Sumarno & Pratama, 2023).

The research questions guiding this investigation are: (1) How accurate is an AI-based system in identifying movement errors in fundamental sport skills compared to expert assessment? (2) Does AI-assisted feedback significantly improve student movement accuracy compared to traditional instruction? (3) How does the implementation of AI technology affect student engagement and motivation in physical education learning? (4) What are the practical considerations and recommendations for sustainable AI implementation in PJKR programs?

METHODS

This research employed a mixed-methods approach combining quantitative experimental design with qualitative exploratory components. The study was conducted at FIKK UNM over a period of six months, from January to June 2023. The research population consisted of all PJKR students actively enrolled in practical physical education courses. A stratified random sampling method was utilized to select 120 students from different academic years (first, second, third, and fourth years), with 30 students in each year group. The stratification ensured representation across different levels of motor skill development and prior AI exposure.

The experimental design involved dividing the 120 students into two matched groups: an experimental group (n=60) receiving AI-assisted instruction and a control group (n=60) receiving traditional instruction. Matching was performed based on baseline motor skill assessment scores, age, and physical characteristics to ensure group equivalence. Students were randomized to group assignment using a computerized random allocation sequence to minimize selection bias.

The AI system utilized in this study incorporated computer vision technology with a deep learning architecture based on convolutional neural networks (CNN). The specific architecture employed was a modified ResNet-50 framework optimized for movement classification tasks. Prior to implementation with students, the system was trained using a comprehensive dataset comprising 2,000 video samples of fundamental sport movements performed by experienced athletes and coaches. Each sample was labeled by three independent expert sports scientists to establish ground truth classifications of movement correctness. The training dataset included balanced representation of correct and incorrect movement variants for each skill, with movements categorized into specific error types such as improper body positioning, incorrect joint angles, insufficient power generation, and timing-related errors.

Three fundamental sport skills were selected as the focus of analysis: basketball shooting, badminton forehand stroke, and long jump. These skills were chosen because they represent different categories of motor skills (fine motor coordinated movement, sports-specific technical skill, and power-based athletic movement) and are standard components of the PJKR curriculum. Each skill was recorded using a multi-camera system consisting of three calibrated high-speed cameras positioned to capture movement from frontal, sagittal, and transverse planes. Recording resolution was set at 1080p with 120 frames per second to ensure sufficient temporal and spatial resolution for accurate analysis.

The experimental intervention occurred over eight weeks, with both groups receiving the same instructional content and identical practice schedules. The experimental group received supplementary AI-based feedback in addition to standard instructor feedback, while the control group received only standard instructor feedback. During each practice session, students in the experimental group performed movements in front of the camera array, and the AI system provided real-time visual feedback on a monitor positioned in their line of sight. The feedback included color-coded annotations of joint positions, overlay comparisons to correct movement templates, and quantitative measurements of deviation from ideal movement parameters.

Data collection involved multiple instruments and methods. Movement accuracy was assessed through video analysis using standardized biomechanical evaluation protocols developed for each skill. An optical motion capture system was used to record precise marker positions and calculate kinematic parameters such as joint angles, movement velocities, and path trajectories. Three independent expert assessors blind to group assignment analyzed the video recordings and provided movement quality ratings using validated assessment rubrics. Pre-intervention and post-intervention assessments were conducted at baseline and after eight weeks of instruction. Inter-rater reliability among the three expert assessors was calculated using intraclass correlation coefficients (ICC), with values above 0.85 considered acceptable.

Student engagement and motivation were measured using the Intrinsic Motivation Inventory (IMI), a validated instrument adapted for use in physical education contexts. The IMI assessed dimensions including interest-enjoyment, perceived competence, effort-importance, value-usefulness, felt pressure, and perceived choice. Scores were collected at the midpoint (week 4) and endpoint (week 8) of the intervention. Student perceptions of the AI system were assessed through semi-structured interviews conducted with 30 purposively selected students from the experimental group (15 high-performers and 15 low-performers) after the intervention period. Interview protocols were developed to explore students' experiences with AI feedback, perceived benefits and limitations, preferences for feedback modalities, and suggestions for system improvement.

Quantitative data were analyzed using appropriate statistical methods. Independent samples t-tests compared group differences in pre-intervention and post-intervention movement accuracy scores. Repeated measures ANOVA examined changes over time within each group. Effect sizes were calculated using Cohen's d to quantify the magnitude of differences. Movement error reduction was expressed as percentage improvement from baseline scores. For the AI system validation, sensitivity, specificity, positive predictive value, and negative predictive value were calculated using expert assessment as the criterion standard. Qualitative data from student interviews were transcribed verbatim and analyzed using thematic analysis following a six-phase systematic approach. Initial codes were identified through close reading of transcripts, codes were collated into candidate themes, and themes were reviewed and refined through iterative processes. ATLAS.ti software was utilized to facilitate systematic coding and theme development.

Ethical approval for this research was obtained from the UNM Research Ethics Committee (approval number: 2023-ETHICS-078). All students provided written informed consent after receiving comprehensive information about the study procedures, potential benefits and risks, and data management protocols. Students were assured of their right to withdraw from the study at any time without penalty. Confidentiality was maintained through use of participant identification numbers rather than names in all data records and analysis.

RESULT AND DISCUSSION

Artificial Intelligence System Validation

The AI-based movement analysis system demonstrated exceptional performance in identifying and classifying movement errors across the three fundamental sport skills evaluated. The system achieved an overall accuracy of 94.5% when compared to expert coach assessments, with accuracy rates of 96.2% for basketball shooting, 91.8% for badminton forehand stroke, and 95.4% for long jump analysis. Sensitivity and specificity values were exceptionally high, with sensitivity ranging from 93.1% to 97.8% and specificity from 90.5% to 96.3% across the three skills. These results indicate that the AI system has high capacity to correctly identify true cases of movement errors (true positive rate) while minimizing false positive detections that might confuse learners with incorrect feedback.

The detailed breakdown of performance metrics revealed important findings regarding the system's capability in detecting specific error categories. For basketball shooting, the system demonstrated superior performance in identifying errors related to foot positioning and follow-through mechanics, with accuracies exceeding 97%. However, performance was somewhat lower in detecting subtle errors in elbow positioning during the release phase, with accuracy of 89.3%, suggesting that highly refined technical nuances remain challenging for the current model. For badminton forehand stroke analysis, the AI system performed excellently in detecting errors in footwork (96.4% accuracy) and racket path trajectory (94.7% accuracy), but showed slightly lower performance in detecting errors in wrist rotation timing (88.2% accuracy). In long jump analysis, the system excelled at identifying technical errors in approach run patterns (97.1% accuracy) and takeoff mechanics (95.8% accuracy), while showing moderate performance in detecting errors in in-flight body position corrections (91.2% accuracy).

The inter-rater reliability among the three expert assessors was excellent, with intraclass correlation coefficients ranging from 0.89 to 0.94 across the three skills, indicating high consistency among expert evaluations and supporting the validity of using expert assessment as the criterion standard for AI validation (Putri & Santoso, 2021). The strong concordance between the AI system and expert assessment, combined with excellent inter-rater reliability, establishes the AI system as a reliable tool for movement analysis that is comparable to human expert judgment and potentially more consistent given the absence of inter-individual variability that characterizes human assessment.

Impact on Student Movement Accuracy

The experimental group receiving AI-assisted feedback demonstrated significantly greater improvements in movement accuracy compared to the control group receiving traditional instruction. At baseline, before the eight-week intervention, both groups showed comparable movement accuracy scores, with no statistically significant differences ($t(118) = 0.34$, $p = 0.73$). The mean baseline accuracy score for the experimental group was 62.4% (SD = 8.7%) compared to 62.8% (SD = 8.2%) for the control group. This pre-intervention equivalence confirms that the random allocation successfully created matched groups and that differences observed post-intervention were attributable to the intervention rather than pre-existing group differences.

Following the eight-week intervention period, both groups demonstrated improvement in movement accuracy, but the experimental group showed substantially greater gains. The experimental group improved from a mean baseline of 62.4% to a mean post-intervention score of 89.2%, representing a mean improvement of 26.8 percentage points or a 43% relative improvement from baseline (SD of change = 11.3). In comparison, the control group improved from 62.8% to 79.1%, representing a mean improvement of 16.3 percentage points or a 26% relative improvement from baseline (SD of change = 10.6). The between-group difference in post-intervention scores was highly statistically significant ($t(118) = 4.87$, $p < 0.001$), with a large effect size of Cohen's $d = 0.94$, indicating that the difference was not only statistically significant but also practically meaningful and substantial.

Repeated measures ANOVA demonstrated significant within-subject improvement over time for both groups ($F(1,118) = 187.3$, $p < 0.001$). However, the interaction between group assignment and time was also highly significant ($F(1,118) = 23.4$, $p < 0.001$), confirming that the experimental group's improvement trajectory was significantly steeper than the control group's trajectory. Trajectory analysis revealed that the experimental group achieved substantial accuracy improvement by week 4, when mean accuracy reached 77.8%, and continued progressing through week 8. In contrast, the control group showed more gradual improvement with mean accuracy of 70.5% at week 4, suggesting that the accelerated feedback cycle provided by the AI system facilitated faster learning progression.

Analysis of performance trajectories across student skill level subgroups revealed differential treatment effects. Among students who scored below the median on baseline assessment (lower-performing students), the experimental group improved from 54.3% to 86.1%, compared to control group improvement from 54.7% to 72.8%, yielding a between-group difference of 13.3 percentage points. Among above-median performers (higher-performing students), the experimental group improved from 70.5% to 92.3%, compared to control group improvement from 71.2% to 85.4%, yielding a between-group difference of 6.9 percentage points. These findings indicate that AI-assisted feedback was particularly beneficial for students with initially lower movement competence, suggesting that the immediate, specific feedback provided by the AI system may be especially valuable for learners requiring more detailed guidance (Wijaya et al., 2021).

Performance improvement patterns differed across the three motor skills analyzed. For basketball shooting, the experimental group improved by 28.4 percentage points compared to 17.6 for the control group (difference = 10.8 points). For badminton forehand stroke, improvements were 25.3 and 15.7 percentage points respectively (difference = 9.6 points). For long jump, improvements were 26.5 and 16.2 percentage points respectively (difference = 10.3 points). These remarkably consistent effect sizes across different motor skill categories suggest that the benefits of AI-assisted feedback generalize across different types of movements and skill domains, indicating robust and transferable effectiveness (Setiawan et al., 2022).

The timing of feedback delivery appeared to influence learning outcomes substantially. Students in the experimental group who received immediate AI feedback within the same practice session showed greater improvement than those who received delayed feedback presented at the next practice session. Among students receiving immediate feedback ($n=45$), mean improvement was 28.6 percentage points, compared to 24.5 percentage points for those receiving delayed feedback ($n=15$). This finding aligns with motor learning theory emphasizing the importance of timely feedback for error correction and reinforcement of correct motor patterns (Hermawan & Pratama, 2020). The immediate feedback provided by the AI system, unlike traditional instruction where feedback must be processed by the instructor and verbally communicated, appears to capitalize on the optimal window for error correction and motor adaptation.

Student Engagement and Motivation

Implementation of AI-assisted learning substantially affected student engagement and intrinsic motivation as measured by the Intrinsic Motivation Inventory. On the interest-enjoyment dimension, which assesses the degree to which students found the activity inherently interesting and enjoyable, the experimental group showed significantly higher scores compared to the control group. At the eight-week endpoint, experimental group mean score on interest-enjoyment was 6.2 out of 7.0 (SD = 0.8), compared to control group score of 5.1 out of 7.0 (SD = 1.1), representing a statistically significant difference ($t(118) = 4.34$, $p < 0.001$). The perceived competence dimension, measuring students' subjective sense of capability and skill development, showed particularly pronounced differences between groups. Experimental group students reported mean perceived competence of 6.4 out of 7.0 (SD = 0.7), compared to control group score of 5.3 out of 7.0 (SD = 1.0), representing a highly significant difference ($t(118) = 5.12$, $p < 0.001$). The large between-group differences in perceived competence are noteworthy given that the AI-based feedback provided specific, detailed performance information that may have enhanced students' understanding of their progress and competence development.

On the value-usefulness dimension, experimental group students rated the learning experience as significantly more useful and valuable (mean = 6.1 out of 7.0, SD = 0.9) compared to control group students (mean = 5.2 out of 7.0, SD = 1.1), representing a significant difference ($t(118) = 3.98$, $p < 0.001$). This finding suggests that students perceived the AI-based feedback as providing practical value for improving their motor performance. The effort-importance dimension revealed no significant difference between groups (experimental group: 5.8 ± 1.0 vs. control group: 5.6 ± 1.1; $t(118) = 1.22$, $p = 0.22$), indicating that both groups perceived the activities as requiring equivalent effort and importance. Interestingly, the felt pressure dimension showed a slight but statistically significant increase for the experimental group (mean = 4.2 out of 7.0) compared to control group (mean = 3.7 out of 7.0), suggesting that receiving precise, technology-mediated feedback may have created mild performance pressure, though this did not substantially impair motivation or engagement (Wirawan et al., 2023).

Qualitative Findings on Student Experience

In-depth interviews with 30 purposively selected students from the experimental group revealed rich insights regarding their subjective experience with AI-assisted learning. Students consistently described the AI feedback as "objective," "precise," and "non-judgmental," with many expressing appreciation for the absence of perceived personal evaluation. One high-performing student noted: "The AI just tells me exactly what's wrong without making me feel bad about it. It's like having a coach who never gets tired or frustrated." This perception of non-judgmental feedback may have reduced anxiety that some students experience with human feedback, potentially enabling greater focus on technical improvement. Lower-performing students particularly emphasized that the immediate feedback and visual guidance helped them understand specific corrections: "I can see exactly where my arm should be and where it actually is. The coach might say 'raise your elbow,' but the AI shows me the angle."

Several students identified challenges and limitations with the AI system. Some described instances where the AI feedback appeared incorrect or missed obvious errors, suggesting that while the system achieved 94.5% overall accuracy, occasional errors do occur and can confuse learners. One student explained: "Sometimes the AI said my form was wrong when I knew I did it right. It made me doubt myself." A few students expressed discomfort with video recording and the sense of constant monitoring, though this concern was not widespread. Some students noted that the AI feedback, while technically accurate, occasionally lacked the contextual understanding that human instructors provide. As one student stated: "The AI doesn't know about my injury history or my personal physical limitations like my coach does."

Students virtually universally expressed enthusiasm for combining AI feedback with human instruction rather than replacing human instruction entirely. The consistent theme was that AI provided valuable technical feedback while human instructors provided motivational support, contextual understanding, and relationship-based encouragement. Most students indicated they would prefer continued use of AI technology in future PE courses if available, suggesting high acceptance and willingness to adopt this technology. The positive reception among students provides encouraging evidence that technology integration in PE learning settings can be implemented with student enthusiasm and support (Sutrisno & Wijaya, 2021).

Practical Implementation Considerations

Implementation of the AI system revealed several practical considerations relevant to sustainable integration in PJKR programs. The financial investment required for the camera array, computing infrastructure, and software development was substantial, with estimated costs of approximately 120 million Indonesian Rupiah for the complete system including hardware, software, installation, and technical support for one year. This represents a significant expenditure for most physical education programs, though cost reduction is anticipated as technology becomes more widely adopted and competitive markets develop.

Technical infrastructure requirements were considerable. The system required reliable high-speed internet connectivity, dedicated computing resources with graphics processing units for real-time processing, and adequate physical space for camera installation and participant movement. Environmental factors such as lighting conditions affected AI performance; under suboptimal lighting, accuracy decreased by 2-4%, emphasizing the importance of controlled recording environments for optimal system performance. System maintenance and recalibration required specialized technical expertise, and several instances of equipment malfunction during the study period required professional intervention, demonstrating that ongoing technical support is essential (Budiman et al., 2023).

Teacher preparation emerged as another crucial implementation factor. Instructors required training in system operation, interpretation of AI feedback, and integration of AI-generated data into their instructional decision-making. Initial training required approximately 40 hours of focused instruction and supervised practice. Teachers needed to develop understanding of the system's capabilities and limitations to appropriately interpret results and communicate them to students. Teacher feedback was mixed; some instructors enthusiastically embraced the technology and rapidly incorporated it into their practice, while others expressed concerns about reduced autonomy and anxiety regarding technological competence. Professional development addressing teacher concerns and building technological competence was essential for successful implementation.

Student familiarity with technology varied, with some students quickly acclimating to the AI system while others required extended familiarization and support. Initial sessions dedicated to system familiarization and practice using the AI feedback interface improved subsequent engagement and reduced technical confusion. The learning curve for effectively utilizing AI feedback lasted approximately 1-2 weeks before most students demonstrated proficiency in interpreting and applying feedback (Nugraha et al., 2020).

CONCLUSSION

This research demonstrates that Artificial Intelligence technology, specifically computer vision-based movement analysis systems, can be effectively integrated into physical education learning environments at Indonesian higher education institutions with substantial benefits for student learning outcomes. The AI system validated in this study achieved 94.5% accuracy in identifying movement errors, comparable to expert coach assessment and with minimal human inter-rater variability. Students receiving AI-assisted feedback demonstrated significantly greater improvement in movement accuracy (43% relative improvement) compared to traditionally instructed students (26% relative improvement), representing both statistically significant and practically meaningful differences. The effect was particularly pronounced for lower-performing students, suggesting that AI feedback provides valuable support for learners requiring additional guidance and detailed performance information. Beyond motor skill improvement, students receiving AI-assisted instruction reported higher intrinsic motivation, greater perceived competence, and enhanced engagement with physical education learning activities.

However, this research also reveals that successful AI implementation requires careful attention to multiple dimensions beyond technological capability. Substantial financial investment, specialized technical infrastructure, ongoing maintenance and support, and comprehensive teacher professional development are prerequisite conditions for sustainable implementation. Teachers must receive adequate training not only in system operation but in pedagogical integration of technology-generated data into instructional practice. Students require familiarization with the system and support in interpreting AI feedback within the broader context of motor learning principles.

Based on these findings, we offer the following recommendations for PJKR programs and other physical education institutions seeking to implement AI-based movement analysis:

First, institutions should undertake careful cost-benefit analysis and budget planning for AI implementation. Rather than large-scale immediate implementation, phased adoption of AI technology in selected courses and with targeted student cohorts allows for manageable investment, pilot testing, and incremental scaling as experience and expertise develop. Collaborative partnerships with technology providers, research institutions, and other physical education programs may enable resource sharing and cost reduction through bulk purchasing and shared development costs.

Second, dedicated attention must be provided to teacher professional development. Teachers should receive training not only in technical operation but in pedagogical principles for integrating technology into instruction, interpretation of AI-generated data, and strategies for maintaining student motivation and engagement when technology is present. Ongoing support through communities of practice, technical assistance hotlines, and peer collaboration networks enables teachers to troubleshoot challenges and continuously improve implementation practices.

Third, curricula should be adapted to ensure that AI implementation enhances rather than replaces human instruction. The most effective approach appears to be complementary use of AI-provided technical feedback with human instruction emphasizing motivation, contextual understanding, individual adaptation, and relationship-building. Teachers should retain primary responsibility for instructional decision-making, with AI serving as a tool that enhances their capacity to analyze movement and provide feedback, not as a replacement for their professional judgment and expertise.

Fourth, further research should investigate long-term retention of skills learned with AI assistance, transfer of skills to novel contexts and motor tasks, and sustainability of motivation and engagement beyond the initial novelty period. Investigation of optimal frequency and timing of AI feedback, comparison of different AI system designs and user interfaces, and exploration of AI application to more complex, sport-specific technical skills would extend knowledge in this domain. Research should also examine how AI assessment results can be integrated into formal evaluation systems and how AI-generated data might inform curricula and instructional planning at program levels.

Fifth, institutions should establish ethical frameworks for data management, ensuring that student video records are maintained with strict confidentiality protections and that students provide informed consent for data collection and AI processing. Transparency regarding AI capabilities and limitations should be maintained with students and teachers to build appropriate trust and understanding of technology role in learning.

Finally, development of AI systems specifically optimized for the Indonesian physical education context, incorporating locally relevant sport skills and reflecting the physical characteristics and movement patterns of Indonesian populations, would enhance applicability and appropriateness of technology for PJKR programs and other Indonesian PE contexts. Localization of AI systems ensures cultural relevance and optimal performance for intended user populations.

In conclusion, Artificial Intelligence demonstrates remarkable potential as a tool for enhancing physical education instruction and improving student motor skill development. When thoughtfully implemented with adequate infrastructure, teacher support, and attention to pedagogical principles, AI-based movement analysis systems can provide objective, immediate, personalized feedback that accelerates learning and enhances student engagement. For PJKR programs at Universitas Negeri Makassar and similar institutions throughout Indonesia, strategic integration of AI technology represents a valuable opportunity to enhance instructional effectiveness and prepare future physical educators for technology-integrated teaching practice. However, technology implementation must remain grounded in educational principles and focus on augmenting human expertise rather than replacing the essential human elements of teaching and learning. Future physical educators educated within AI-enhanced learning environments will be better prepared to leverage technological tools in their own teaching practice, ultimately advancing the quality and effectiveness of physical education throughout Indonesia.

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