



## Video-based AI system for automatic range of motion assessment in Physical Education and sport

*Sistema de inteligencia artificial basado en video para la evaluación automática del rango de movimiento en el ámbito de la Educación Física y el deporte*

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### Abstract

**Introduction:** ROM is a critical indicator of musculoskeletal health, flexibility, and motor performance, yet its assessment in schools has been constrained by manual methods such as goniometers, which are time-intensive, subjective, and impractical for large groups. **Objective:** This study aimed to develop and validate a video-based artificial intelligence (AI) system for automatic Range of Motion (ROM) assessment in physical education.

**Methodology:** Leveraging advances in AI and computer vision, particularly pose estimation algorithms such as MediaPipe and OpenPose, this research designed a system capable of capturing and analyzing joint movements through standard video recordings on smartphones and laptops. Using the 4D Holistic Model (Define, Design, Develop, Disseminate), the study systematically identified teacher needs, built a prototype with automated angle calculation and real-time feedback, and conducted iterative expert validation and classroom pilot testing.

**Results:** The results demonstrated that the system provides accurate, efficient, and user-friendly assessments while reducing teacher workload and enhancing instructional precision. This finding is corroborated by a survey result value of 4.16, which indicates that the respondents were satisfied or satisfied, and a significance value of greater than 0.05, which indicates that there is no significant difference. Practical implementation highlighted benefits for both teachers through streamlined monitoring and individualized instruction and students, who gained objective progress feedback and improved motivation.

**Discussion:** While challenges remain regarding lighting conditions, teacher readiness, and data privacy, the system represents a cost-effective and scalable innovation for integrating AI into physical education.

**Conclusions:** The findings underscore its potential to transform assessment practices, foster physical literacy, and support healthier student development in school contexts.

### Keywords

Artificial intelligence; educational technology; primary education; pose estimation; sports biomechanic.

### Resumen

**Introducción:** El rango de movimiento (ROM) es un indicador fundamental de la salud musculoesquelética, la flexibilidad y el rendimiento motor, pero su evaluación en las escuelas se ha visto limitada por métodos manuales como los goniómetros, que requieren mucho tiempo, son subjetivos y poco prácticos para grupos grandes.

**Objetivo:** El objetivo de este estudio era desarrollar y validar un sistema de inteligencia artificial (IA) basado en video para la evaluación automática del rango de movimiento (ROM) en la educación física.

**Metodología:** Aprovechando los avances en IA y visión artificial, en particular los algoritmos de estimación de posturas como MediaPipe y OpenPose, esta investigación diseñó un sistema capaz de capturar y analizar los movimientos articulares a través de grabaciones de video estándar en teléfonos inteligentes y ordenadores portátiles. Utilizando el modelo holístico 4D (definir, diseñar, desarrollar, difundir), el estudio identificó sistemáticamente las necesidades de los profesores, construyó un prototipo con cálculo automático de ángulos y retroalimentación en tiempo real, y llevó a cabo una validación iterativa por parte de expertos y pruebas piloto en el aula.

**Resultados:** Los resultados demostraron que el sistema proporciona evaluaciones precisas, eficientes y fáciles de usar, al tiempo que reduce la carga de trabajo de los profesores y mejora la precisión de la enseñanza. Este hallazgo se ve corroborado por un valor de 4,16 en la encuesta, lo que indica que los encuestados estaban satisfechos o muy satisfechos, y un valor de significación superior a 0,05, lo que indica que no hay diferencias significativas. La implementación práctica puso de relieve los beneficios tanto para los profesores, gracias a la optimización de la supervisión y la instrucción individualizada, como para los alumnos, que obtuvieron una retroalimentación objetiva sobre su progreso y una mayor motivación.

**Discusión:** Aunque siguen existiendo retos en cuanto a las condiciones de iluminación, la preparación de los profesores y la privacidad de los datos, el sistema representa una innovación rentable y escalable para integrar la IA en la educación física.

**Conclusiones:** Los resultados subrayan su potencial para transformar las prácticas de evaluación, fomentar la alfabetización física y apoyar un desarrollo más saludable de los alumnos en el contexto escolar.

### Palabras clave

Educación primaria; estimación de la postura; biomecánica deporte; inteligencia artificial; tecnología educativa.

## Introduction

Physical education plays a crucial role in supporting the holistic development of students (Keim, 2024), making significant contributions to their motor skills, physical fitness, and overall health (Lee et al., 2023). A critical component within this framework is the evaluation of motor development, particularly through assessing Range of Motion (ROM) (Brogan et al., 2022). ROM measures the maximum movement capacity around specific joints, serving as a vital indicator of students' physical flexibility, muscle strength, and joint health (Parati et al., 2023). Accurate assessment of ROM not only aids in identifying physical limitations and potential injury risks (Farhan et al., 2022), but also guides teachers in designing appropriate and individualized training activities that enhance students' physical performance and well-being (Yumi, 2023).

Traditionally, ROM assessment in educational settings relies heavily on manual approaches, typically employing tools such as goniometers (Brogan et al., 2022). Although these methods are well-established (Ore et al., 2020), they pose several significant limitations, including the need for specialized training, subjectivity, inconsistency, and time-intensive procedures, especially when applied to large student groups in school environments (Nithya et al., 2022). Consequently, teachers often find it challenging to incorporate regular and comprehensive ROM assessments into their curricula, limiting their ability to systematically monitor and support each student's physical development (Miranda, 2025).

The rapid evolution of artificial intelligence (AI) and computer vision technologies offers promising solutions to overcome these traditional constraints (Kinoshita & Komatsu, 2023). Recent advancements in AI-driven pose estimation techniques (Sun et al., 2025), particularly those using deep learning frameworks like OpenPose and MediaPipe (Lin et al., 2025), have transformed human motion analysis by enabling automatic, accurate, and real-time assessments of human postures and movements through standard video recordings (Necibi et al., 2025). Despite widespread adoption in professional sports training and clinical rehabilitation, the potential application of these technologies within the context of school-based physical education remains underexplored, particularly in Indonesia.

Addressing this gap, the current research aims to develop and validate an innovative video-based AI system specifically tailored for automatic ROM assessment in educational settings. This system leverages standard camera technologies available on laptops, eliminating the need for expensive and complex equipment. By automating the process of capturing and analyzing student movements during physical education activities such as squats, lunges, and shoulder flexion exercises, the developed system promises greater accuracy, efficiency, and ease of use. Furthermore, it facilitates real-time feedback, allowing educators to quickly identify and address students' specific motor development needs and adapt their instructional strategies accordingly.

The novelty of this study resides in three critical aspects. First, it introduces an accessible, cost-effective AI-driven ROM assessment method suitable for large-scale deployment in schools. Second, the developed AI models are specifically trained to evaluate the motor skills of children and adolescents in typical educational contexts, distinct from clinical or high-performance athletic environments. Finally, the research emphasizes practical validation and real-world applicability, involving educators and students directly in the system's iterative design, testing, and refinement processes.

Through this research, it is anticipated that the integration of AI and video-based ROM assessments will significantly enhance the effectiveness of physical education programs by providing educators with accurate, real-time, and individualized assessment tools. Ultimately, this advancement supports more informed teaching practices, fosters improved student physical performance, and contributes positively to long-term student health and well-being.

## Method

### *Participants*

This study encompassed two educational institutions of varying levels: an elementary school and a middle school. The sample size from each school was limited to 5, yielding a total of 10 samples. The re-



searchers conducted this due to the study being in the first field trial phase of the produced tool, therefore deeming a small sample size adequate as it had not yet progressed to the generalization stage. Conversely, researchers also conducted a survey of physical education instructors with more than 10 years of teaching experience at both institutions to assess the produced application.

The sample characteristics of this study consist of five elementary school students and five middle school students. The average weight of the elementary school pupils is  $24.28 \pm 2.06$  kg, and their average height is  $110.60 \pm 3.05$  cm. They are between the ages of 6 and 9. Middle school students, who are 14-15 years old, have an average weight of  $50.46 \pm 6.14$  kg and a height of  $160 \pm 9.25$  cm.

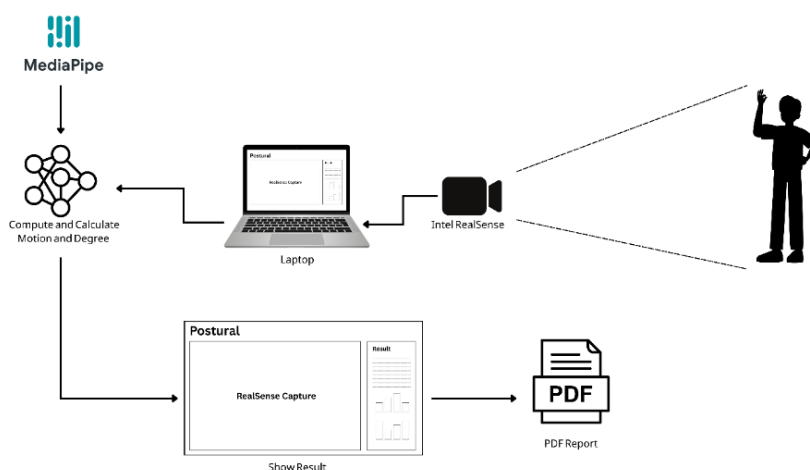
### Procedure

The research approach commenced with the implementation of the produced tool innovation, encompassing application preparation, camera placement, and calibration. The application was prepared by connecting a laptop to an external camera, namely the Intel RealSense D435i at 30 FPS. The researcher was required to put the camera at a height of 104 cm and at a distance of 3 meters from the subject being measured. The object and camera must be situated in a well-lit area that is neither excessively bright or exposed to direct sunlight. It is crucial to acknowledge that the measurement device employed in the procedure utilizes digital technology, which is susceptible to extreme heat. Consequently, researchers must account for this to ensure the measurement procedure operates optimally. Upon completion of the device installation, the researcher directs the subject to perform various Range of Motion (ROM) movements for measurement. The motions executed by the assessed person encompass abduction, flexion, and hip actions. The patient executed these movements three times to ascertain their range of motion level.

### Research and Development Models

This research applies a Research and Development (R&D) methodology using the 4D Holistic Model, which includes four stages: Define, Design, Develop, and Disseminate. The primary aim is to create, validate, and implement an innovative artificial intelligence (AI)-based system capable of automatically assessing Range of Motion (ROM) in physical education contexts using video capture technology. The integration of tools such as MediaPipe, Intel RealSense camera, and custom-built software ensures that the system is not only accurate but also user-friendly for educators, researchers, and practitioners (figure 1).

Figure 1. Working Flow



### Define Stage

The Define stage begins with a comprehensive needs analysis, identifying the existing challenges in ROM assessment within physical education and sport. Traditionally, ROM is measured manually by instructors using goniometers or visual observation, which can be time-consuming and subject to human error.

Through literature reviews, expert interviews, and field observations, the researchers established the need for a video-based AI system that can streamline measurement processes, enhance accuracy, and provide real-time feedback. In addition, the requirements of physical education teachers and students were gathered to ensure that the system aligns with practical needs in classroom and training environments.

### *Design Stage*

In the Design stage, the conceptual framework of the system was developed. As illustrated in Figure 1, the proposed workflow integrates several components. The Intel RealSense camera captures live video of the subject performing specific physical movements. This visual data is transmitted to a laptop where MediaPipe 0.10.21., an open-source framework for building multimodal AI pipelines, processes the input. MediaPipe's algorithms compute and calculate key joint positions, motion patterns, and angles relevant to ROM assessment. The captured data is then visualized through a postural interface that shows real-time results, including joint degree measurements and postural alignment. Importantly, the system also includes a reporting function that automatically generates a PDF report, enabling instructors to keep structured records of student assessments.

### *Develop Stage*

The Develop stage involves iterative prototyping, testing, and refinement of the system. The software was programmed to detect key human skeletal points, calculate angular motion, and evaluate results against standard ROM benchmarks. The development also focused on ensuring usability by creating a clear and accessible graphical user interface (GUI) that allows teachers to operate the system with minimal technical expertise. Pilot testing was conducted in controlled settings with participants performing standardized physical tasks, such as arm flexion, shoulder abduction, and leg extension. Feedback from these trials guided system improvements, particularly in motion capture precision, calibration settings, and the accuracy of angle calculations. To ensure reliability, multiple test-retest sessions were conducted, comparing AI-generated results with conventional goniometric measurements.

### *Disseminate Stage*

The Disseminate stage focuses on the implementation and distribution of the final product. The validated system was introduced in educational settings, particularly in physical education classes, to evaluate its practicality in real-world environments. Teachers were trained to operate the system, interpret results, and utilize the PDF reports for student performance tracking. Findings and insights from this phase were shared through workshops, academic conferences, and journal publications to ensure broader adoption. In addition, dissemination involved preparing guidelines and training materials so that institutions and practitioners can independently implement the system in their own contexts.

## **Data analysis**

The IBM SPSS Statistic 25 software was employed by the researcher to conduct statistical testing of the data that had been collected through field or school trials. The objective of this analysis is to ascertain the descriptive values of the data that has been collected. Furthermore, a difference test will be implemented on the three trials to ascertain the discrepancy in their values. The consistency of the ROM measurement instrument innovation that has been developed can be ascertained through the results of this analysis.

## **Results**

This study presents the research findings in a series of sections, which are elucidated as follows.

### ***The Result of Development Process***

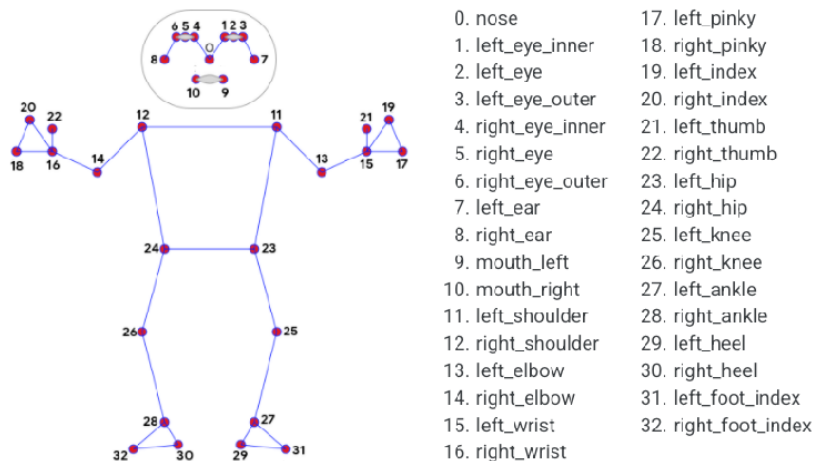
#### *Stage 1: Define*

The Define phase begins by thoroughly identifying and analyzing the specific needs, problems, and challenges faced by physical education (PE) teachers in conducting ROM assessments within school environments. This stage involves conducting an extensive literature review on existing ROM assessment



techniques, AI-driven pose estimation methods, and MediaPipe video-based analysis technologies (Figure 2). Additionally, field observations are carried out in selected primary and secondary schools to gain direct insight into current assessment practices, limitations, and logistical constraints. Complementing these efforts, semi-structured interviews and structured questionnaires are administered to PE teachers, collecting qualitative data on their experiences, needs, expectations, and technical requirements. The expected outcome of this phase is a comprehensive report detailing the specific requirements, practical considerations, and clearly defined objectives that will inform the subsequent design and development stages.

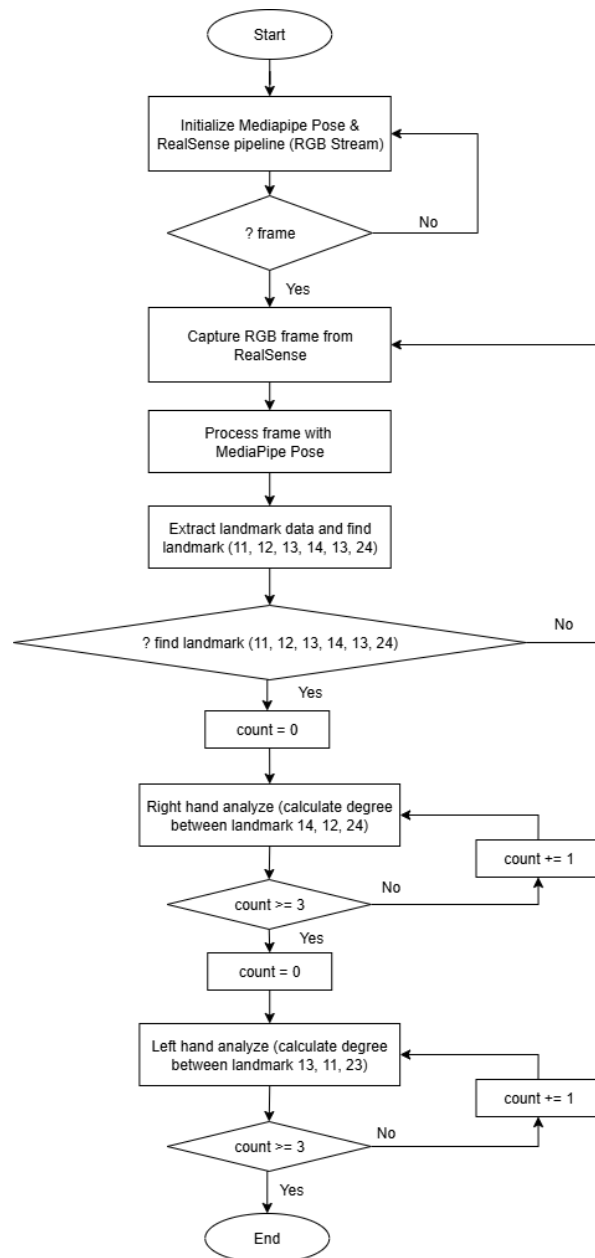
Figure 2. Landmark MediaPipe



### Stage 2: Design

The second phase, Design, involves translating insights gained from the Define phase into a detailed technical and practical blueprint for the ROM assessment system (Figure 1). This includes designing the overall system architecture, determining essential technical specifications, establishing data workflows, and integrating advanced AI pose estimation algorithms, such as OpenPose or MediaPipe, suitable for ROM measurements. Concurrently, a prototype of the ROM assessment system is developed, featuring an intuitive user interface (UI), real-time video capturing capabilities, automated ROM angle calculations, and clear visual representations of results (Figure 3). In addition, initial validation criteria and evaluation procedures are carefully planned to ensure the system meets both educational standards and technological benchmarks. The intended outcome of this phase is the production of an operational initial prototype ready for preliminary expert review and real-world user testing.

Figure 3. Abduction Flowchart



### Stage 3: Develop

The third phase, Develop, emphasizes extensive validation, testing, and refinement of the developed ROM assessment prototype (Figure 4). Initially, the system undergoes expert validation involving multidisciplinary panels, including biomechanics specialists, physical education experts, and educational technology researchers. These experts assess the prototype's accuracy, technical reliability, usability, and alignment with educational contexts. Following expert validation, pilot testing is conducted in real PE class scenarios, involving both teachers and students performing common physical activities, such as squats, lunges, and shoulder flexions. The main goal of pilot testing is to evaluate the system's practical accuracy, real-time performance, ease of use, and overall effectiveness in capturing relevant ROM data. Throughout this phase, structured user feedback is systematically collected and analyzed, driving iterative enhancements in the AI algorithms, user interface, system features, and overall usability. The expected outcome is a refined, validated, and user-friendly system demonstrating high accuracy, practical applicability, and positive acceptance by teachers and students.

Figure 4. Coding Development Process

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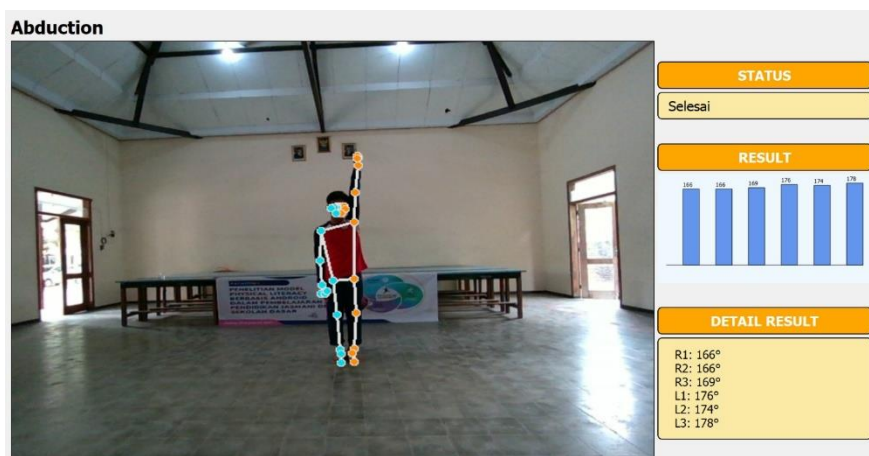
260     max_value = max(self.values) if max(self.values) > 0 else 1
261
262     # Sumbu X
263     painter.setPen(QtCore.Qt.black)
264     painter.drawLine(left_margin, height - bottom_margin,
265                    width - right_margin, height - bottom_margin)
266
267     # Gambar bar
268     for i, value in enumerate(self.values):
269         bar_height = int((value / max_value) * bar_area_height)
270         x = left_margin + (2 * i + 1) * bar_width
271         y = height - bottom_margin - bar_height
272         rect_bar = QtCore.QRect(x, y, bar_width, bar_height)
273
274         painter.setBrush(QtGui.QBrush(QtGui.QColor(100, 149, 237)))
275         painter.setPen(QtGui.QPen(QtGui.QColor(Qt.black, 1)))
276         painter.drawRect(rect_bar)

```

### Stage 4: Disseminate

Finally, the Disseminate phase focuses on the implementation, broad distribution, and effective utilization of the ROM assessment system within educational settings (Figure 5). The finalized version of the system is produced and disseminated widely among partner schools. To ensure successful integration and adoption, comprehensive training modules, including instructional manuals and practical video tutorials, are developed specifically for physical education teachers. Additionally, structured workshops and hands-on training sessions are conducted to empower educators in independently and effectively using the system in their classrooms. Long-term evaluations are performed to document the system's impact on teaching quality, student motor skill assessments, and overall instructional practices. Furthermore, research outcomes are disseminated through publication in reputable international academic journals and presented at relevant educational conferences. The ultimate goal of this stage is to achieve widespread adoption of the system, thereby improving physical education assessment practices, enhancing student motor development outcomes, and contributing valuable insights to the academic and educational community.

Figure 5. Abduction Motion Detection Result



### Statistical Analysis

In order to ascertain the consistency of the ROM measurement instrument innovation that was developed, researchers conducted statistical analysis. It is a common occurrence in research for the interpretation of the data from the analysis results to differ from the interpretation of the data from the t-test results. The ANOVA test was implemented to execute the difference test in this investigation. A difference is pronounced to exist in the ANOVA test if the p-value is less than the significance level of 0.05. Consequently, the interpretation of the data in Table 1 is not to identify differences, but rather to identify similarities, as per the previous explanation.

The ANOVA test results indicated that there was no statistically significant difference in the movement assessment scores among the three trials. These results are demonstrated by all three variables (abduction, flexion, and hip), both right and left, with a p-value of greater than 0.05. This suggests that the movement assessment, which was conducted using the innovative ROM measurement instrument, yielded favorable results. The equation depicted in Table 1 demonstrates that this application is highly reliable in its assessment of students' ROM. However, the measurement results indicate a substantial disparity in measurement outcomes when compared to the mean values. The mean value difference between the first and second measurements of right abduction was 9.20. The first and second measurements for right flexion exhibited a comparable trend, with a mean value difference of 18.00. In general, the ROM measurement tool has effectively provided data that can be used as a foundation for evaluation by physical education instructors for students in schools.

Table 1. Result of the Statistical Analysis

Item Test		Mean	SD	p-Value
Right Abduction	RA1	170.40	5.92	0.55
	RA2	161.20	26.55	
	RA3	167.30	5.69	
Left Abduction	LA1	169.10	9.38	0.30
	LA2	165.10	7.95	
	LA3	167.50	7.45	
Right Flexion	RF1	168.40	7.87	0.44
	RF2	150.40	50.34	
	RF3	166.20	7.78	
Left Flexion	LF1	161.40	17.68	0.71
	LF2	166.80	6.03	
	LF3	163.90	6.33	
Right Hip	RH1	52.10	20.57	0.96
	RH2	52.50	24.41	
	RH3	54.70	22.61	
Left Hip	LH1	55.30	20.64	0.89
	LH2	59.40	23.70	
	LH3	55.10	21.33	

### User Experience

The survey, which was conducted among two physical education instructors at two designated schools, produced favorable outcomes. The experiences of both physical education teachers were satisfactory, as evidenced by their ratings within the range of 3-5. This outcome demonstrates the application's effectiveness in terms of both quantitative and qualitative data.

Table 2. User Experience

Item Code	Statement	PE Teacher A	PE Teacher B	Score
A. Ease of Use				
A1	Easy Installation.	5	4	4.50
A2	Understandable Appearance.	5	3	4.00
A3	Intuitive Steps.	4	4	4.00
A4	Easy to Learn.	5	4	4.50
A5	The Result is Readable.	4	3	3.50
B. Usefulness & Functionality				
B1	Useful Data.	5	5	5.00
B2	More Efficient.	4	4	4.00
B3	The features are already sufficient.	3	4	3.50
B4	Precise Data.	4	3	3.50
B5	Feedback Support.	5	4	4.50
C. Overall Perception				
C1	Satisfied with The Performance.	4	4	4.00
C2	Will Recommend.	5	3	4.00
C3	Intending to Use.	5	4	4.50
Average				4.16



## Discussion

Physical education is crucial in the development of a child's motor abilities through a structured learning process. Conversely, physical education instruction contributes to students' psychological and physiological wellness. This function has resulted in the development of a variety of learning approaches and innovations in physical education. The objective of this research is to create a novel instrument for evaluating the Range of Motion (ROM) of students in physical education classes.

The research findings demonstrate that the ROM tool innovation is capable of accurately measuring the range of motion of physical education students in both elementary and middle institutions. This conclusion is corroborated by quantitative data that exhibits a significance value greater than 0.05, suggesting that the range of motion was consistently measured across three trials. Furthermore, qualitative data in the form of a survey conducted with two physical education teachers who have accumulated approximately ten years of professional experience substantiates these findings. The survey results suggest that the physical education instructors are satisfied with their experience in implementing the ROM tool innovation, as indicated by a score of 4.16.

Significant results regarding innovation in ROM measurement are also demonstrated in numerous pertinent studies. Research conducted by Theile et al., (2022) has demonstrated that the iPhone goniometer application is a reliable method for measuring the range of motion of a person's hand (finger), similar to a traditional goniometer. In addition, research conducted by Soeters et al., (2023) utilized a ROM measurement application known as PeerWell to demonstrate additional innovations. The results of this study demonstrated the effectiveness of remote measurement of the range of motion (ROM) of the shoulder joint. In addition, there is additional pertinent research that demonstrates innovation in the measurement of lower limb joints using smartphones, as conducted by Miyachi et al., (2022). The study's findings suggest that the straight leg raise angle and the hip internal rotation angle are highly reliable measurements. In addition, the investigation established a robust correlation between the conventional method and the developed method.

### ***The Significance of Range of Motion (ROM) in Physical Education***

Range of Motion (ROM) is a cornerstone indicator of musculoskeletal health and physical readiness (Faridah et al., 2022), especially within school-based physical education contexts. Assessing ROM provides teachers with an evidence-based lens to evaluate flexibility, joint health, and muscular balance among students. Unlike generic measures of physical fitness such as endurance or strength, ROM reflects a nuanced understanding of how well students can perform functional movements like squats, lunges, and shoulder rotations (Arif et al., 2023). These measures are not only critical for immediate physical education instruction but also predictive of long-term health outcomes. Restricted ROM is often associated with poor posture (Jung et al., 2012), heightened risk of injury, and barriers to engaging in various sports and daily activities.

Traditionally, ROM assessments relied heavily on manual techniques such as goniometers (Praveen et al., 2024). While well-established, these methods are not feasible in modern classrooms with large student groups due to their time-intensive nature and requirement for specialized expertise. Teachers often find it impractical to systematically administer these assessments, which results in missed opportunities to detect developmental asymmetries or functional limitations early. Moreover, inter-rater variability and measurement subjectivity further compromise the reliability of manual assessments.

This study positions ROM assessment as a transformative tool when integrated with digital and AI-driven technologies. By leveraging video-based analysis through standard cameras, educators can bypass the need for specialized equipment and still achieve accurate, reliable, and real-time insights. In doing so, ROM evolves from being a sporadic, resource-heavy task to a continuous, accessible measure integrated into everyday learning.

Furthermore, ROM in children and adolescents carries psychosocial implications. Students with restricted flexibility or motor limitations may experience reduced confidence, hesitancy to engage in



group activities, and decreased physical literacy. By embedding ROM monitoring into PE curricula, educators foster inclusivity and targeted support, enabling all students to progress according to their capabilities.

Ultimately, the emphasis on ROM extends beyond physical education and intersects with public health, injury prevention, and the cultivation of lifelong physical literacy. The innovation in this manuscript, therefore, responds to a dual imperative: enhancing immediate teaching effectiveness and safeguarding long-term student well-being through systematic and scalable ROM assessment practices.

### ***AI and Video-Based Assessment as a Disruptive Innovation***

The integration of artificial intelligence (AI) and computer vision into ROM assessment (Dallinga et al., 2017), represents a paradigm shift for physical education. Traditionally bound by manual measurement tools, assessment is now being revolutionized by AI's ability to automate, standardize, and scale procedures that once relied heavily on human expertise (Takigami et al., 2024). By deploying pose estimation frameworks like OpenPose and MediaPipe, this study illustrates how AI can capture and analyze human motion with remarkable precision using only video input from everyday devices such as smartphones or laptops.

This innovation introduces three disruptive qualities. First, accessibility: by eliminating the dependency on costly, specialized equipment, the technology democratizes access to advanced biomechanical assessment. Schools with limited budgets or resources can now employ methods once exclusive to sports laboratories or clinical rehabilitation settings. Second, efficiency: teachers no longer need to dedicate extensive time to individual measurements; AI can process group assessments in real time, freeing educators to focus on pedagogy. Third, objectivity: AI systems mitigate human error and bias, ensuring that assessments remain consistent regardless of the assessor's level of expertise.

The AI-driven system also strengthens the feedback loop in physical education (Li & Xue, 2023). Instead of delayed feedback from sporadic manual tests, real-time results empower teachers to adapt instructions dynamically during classes (Chen, 2025). For instance, if a student demonstrates limited hip mobility during lunges, teachers can immediately introduce stretching or corrective exercises. This responsiveness enhances the personalization of instruction and fosters more effective motor learning.

Moreover, the system aligns with global educational trends emphasizing digital transformation and the incorporation of smart technologies in classrooms. As schools transition toward hybrid and technology-rich environments, the introduction of AI-based physical education tools affirms that PE, often seen as resistant to digitalization, can equally benefit from innovation (Vogt et al., 2019).

However, the integration of AI into education also invites critical reflection (Hsia et al., 2023). Issues surrounding data privacy, ethical use, and teacher readiness must be addressed to ensure that the technology serves pedagogical goals responsibly (Tian, 2024). This manuscript's emphasis on cost-effectiveness and school-centered validation suggests a strong awareness of these factors, positioning the project as both disruptive and pragmatically grounded in educational realities.

### ***Development Process Using the 4D Holistic Model***

The research employed the 4D Holistic Model (Define, Design, Develop, Disseminate), providing a robust framework for systematic development and validation of the ROM system. Each phase contributed uniquely to shaping a practical, innovative, and contextually responsive tool.

The define phase was crucial in identifying gaps between existing ROM assessment practices and classroom realities. By combining literature reviews, field observations, and teacher interviews, the study generated a nuanced understanding of the logistical and pedagogical barriers teachers face. This ensured that the project did not merely replicate laboratory models but directly responded to the educational context.

The design phase transformed these insights into a system blueprint. By integrating MediaPipe pose estimation, real-time video capture, and automated angle calculations, the researchers produced a prototype aligned with both technological feasibility and classroom usability. Importantly, this stage also planned for intuitive interfaces, critical since teachers may not possess advanced technical skills.



The develop phase operationalized the prototype through iterative testing and validation. Expert panels from biomechanics, physical education, and educational technology assessed accuracy and alignment with curricular needs. Pilot trials in classrooms provided real-world insights, with structured teacher and student feedback driving refinements. This cyclical process illustrates a commitment to co-creation, ensuring that end-users shaped the tool's evolution rather than passively receiving it.

The disseminate phase underscored scalability and sustainability. By producing training modules, workshops, and tutorials, the project recognized that adoption depends not only on technological readiness but also on teacher empowerment. Additionally, dissemination through schools, publications, and conferences ensures visibility, peer validation, and broader uptake.

Altogether, the 4D model illustrates that successful educational technology development requires more than technical innovation; it demands context sensitivity, iterative validation, and sustainable integration strategies. By systematically bridging these dimensions, the project provides a replicable roadmap for future educational AI interventions.

### ***Practical Implications for Teachers and Students***

The introduction of a video-based AI ROM assessment system carries profound implications for teachers and students alike (Lee & Kim, 2025). For teachers, the system simplifies the assessment process while enhancing instructional precision (Wu et al., 2025). No longer burdened by manual measurements or inconsistent observations, educators can rely on automated data to guide lesson planning. For example, identifying widespread limitations in shoulder flexion across a class may prompt curriculum adjustments emphasizing flexibility and injury prevention.

The system also elevates the role of teachers as facilitators of individualized learning. Instead of one-size-fits-all instruction, teachers can differentiate activities based on students' unique ROM profiles. This aligns with inclusive education principles, ensuring that students with varying abilities receive tailored support. The immediacy of real-time feedback also strengthens classroom dynamics: corrective guidance can be delivered during practice, enhancing motor skill acquisition and reducing the likelihood of harmful compensatory movements (Zhang & Wang, 2024).

For students, the benefits extend beyond improved motor performance (Laughlin et al., 2019). AI-driven assessments provide objective recognition of progress, which can enhance motivation and self-efficacy. Students who see measurable improvements in their ROM are likely to develop greater confidence in their physical capabilities. Moreover, the technology introduces an element of engagement; digital interfaces and visual feedback can make assessments more interactive and relatable for digitally native learners (Sargent & Calderón, 2021).

The implications also extend to health and well-being (Holzgreve et al., 2020). By systematically monitoring ROM, schools can identify students at risk of musculoskeletal issues early and intervene appropriately. Over time, such practices contribute to the cultivation of healthier, more active lifestyles. Importantly, the integration of AI into physical education signals to students that technology is not confined to academic subjects, but also enhances physical and health domains, reinforcing the holistic value of education (Lee & Lee, 2021).

However, successful implementation requires ongoing teacher training and institutional support. Without sufficient professional development, teachers may struggle to harness the system's full potential. Thus, the project's emphasis on training workshops and tutorials is not just supplementary but essential to ensuring that practical benefits translate into classroom realities.

### ***Challenges, Limitations, and Future Directions***

While the study demonstrates significant innovation, it also surfaces challenges and limitations that merit consideration. One key issue is accuracy under varied conditions. Video-based AI systems may perform inconsistently under poor lighting, crowded classrooms, or unconventional movement patterns. Ensuring robustness across diverse school environments remains a developmental priority.

Another challenge is teacher readiness. Not all educators may feel comfortable integrating AI tools into their pedagogy. Resistance may stem from limited digital literacy, concerns about workload, or apprehension about technology replacing professional judgment. Addressing these concerns through structured training and continuous support is vital.



Data privacy and ethics constitute another layer of complexity. Capturing and storing student video data necessitates strict safeguards to ensure compliance with ethical and legal standards. Parents, students, and school administrators must be assured that the system prioritizes confidentiality and responsible use.

Financial sustainability also requires attention. While the system reduces costs compared to laboratory equipment, initial implementation may still pose barriers for under-resourced schools. Partnerships with ministries of education and technology providers could help subsidize adoption and ensure equitable access.

Looking ahead, future directions include expanding the system's analytical scope beyond ROM to encompass posture analysis, gait assessment, and injury risk prediction. Integration with wearable technologies could further enrich data accuracy. Additionally, AI-driven personalization could evolve into adaptive training programs that dynamically adjust to each student's performance trends.

Research dissemination should also continue to bridge the gap between innovation and practice. Longitudinal studies documenting the system's impact on student outcomes, teacher practices, and overall physical education quality will strengthen its credibility and influence policy adoption.

In summary, while challenges remain, the project charts a clear path forward. By acknowledging limitations and proposing future trajectories, the study positions itself not as a final solution but as a critical step in the ongoing evolution of technology-enhanced physical education.

## Conclusions

Range of Motion (ROM) makes a vital contribution to a child's development. In the context of physical education, ROM is one of the tools used to identify a student's skills. ROM is essential for physical education teachers when providing targeted, comfortable, and safe physical education lessons for students. The conceptual integration of ROM in physical education has a comprehensive impact on the physical education learning process. Teachers and students, as the implementers of the learning process, feel the significant positive impact when this integration occurs.

This study has attempted to develop a motion analysis application, specifically related to ROM. The developed application successfully measures ROM and demonstrates significant measurement results. However, evaluation and refinement of this application are still needed. Several shortcomings in the developed application must be adjusted immediately to provide more relevant and precise analysis results.

On the other hand, this research has also succeeded in digitizing physical education through the innovative development of an artificial intelligence (AI)-based video analysis application. This innovation has advanced the physical education learning process and created a comfortable and attractive learning environment. The implementation of ROM analysis results on students during the physical education process will help teachers provide a learning process that suits the needs of students. Students will also receive positive impacts in the form of improved performance, as a result of learning that is tailored to their needs. Physical education teachers' concerns regarding injuries can also be minimized through understanding and knowledge gained from ROM analysis. Thus, the physical education learning process is not only about activities aimed at health and fitness, but also about developing students' motor skills in a measurable and targeted manner.

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