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Enhancing Adolescents' Physical Education Self Efficacy Through Artificial Intelligence Supported Feedback

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Abstract. Artificial intelligence can provide individualized movement information at a frequency that is difficult to achieve through teacher observation alone. This study examined whether AI-supported corrective feedback could strengthen adolescents' physical education self-efficacy while improving movement execution. Eighty-four students aged 13–15 completed an eight-week controlled experiment involving bodyweight squats, forward lunges, and countermovement jumps. The AI group received pose-estimation-based feedback generated with MediaPipe Pose Landmarker and OpenCV, whereas the control group received standardized teacher feedback. The AI group increased self-efficacy from 4.17 ± 0.62 to 5.39 ± 0.56 points, compared with 4.19 ± 0.60 to 4.66 ± 0.61 in the control group, producing a significant group × time interaction, $F(1,82) = 42.31$, $p < .001$, $\eta p^2 = .340$. Movement scores increased from 64.1 ± 6.8 to 82.3 ± 5.7 in the AI group. Within the AI condition, movement-score improvement and feedback engagement jointly predicted post-intervention self-efficacy, adjusted $R^2=.487$. The findings indicate that interpretable, attempt-specific AI feedback can make mastery progress more visible and support both technical learning and efficacy beliefs in adolescent physical education.

Keywords: artificial intelligence, physical education, self-efficacy, adolescents, intelligent feedback

1. Introduction

Physical education is a unique learning domain where competence is easily observable, repetitions happen under time pressure, and teenagers evaluate their competencies based on immediate movement results. Thus, digital technology becomes more and more important for physical education [1]. Studies about video feedback show that visual information helps to learn a motor skill when learners can relate a detected mistake with a corresponding correction [2]. Moreover, meta-analytical evidence suggests using corrective feedback in motor skills learning [3]. Motion analysis software was even included in middle-school skill teaching practice, showing the possibility of augmentative feedback based on digital technologies in a natural class setting [4].

In school PE lessons, the limitation of instructing is especially acute in the case of one teacher who needs to observe many movements in repetition. The delayed feedback may reduce the link between a mistake and a correction, while overly general feedback may not specify what exact kinematic component should be corrected. With the help of the camera-based AI system, the

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feedback loop can be shortened, since mistakes at the joint level can be detected immediately after the movement. If this feedback is comprehensible and followed by the next repetition, learners will see the effect of suggested correction, thus creating a ground for mastering-related self-efficacy.

The psychological side is also important. Self-efficacy is associated with effort and perseverance and is developed due to successful experience of completing the tasks and instructional support [5]. Auto-assessment assisted by AI is the method to create such experiences by transforming movement traces into individual performance information [6]. Digital motor-competence assessment assists in actionable visual feedback [7]. However, there are many examples of technology-based AI applications that do not have much psychological evidence [8]. Recent research on real-time pose recognition reveals the potential of feedback for supporting the movement quality and self-directed learning [9]. Iterative feedback cycles are considered in digital formative assessment studies [10]. Thus, the current study aims to find out if the feedback based on pose estimation can increase adolescents' self-efficacy by providing visible improvement of mastery.

2. Literature review

2.1. Self-efficacy in adolescent physical education

Self-efficacy in physical education is an individual's conviction about being able to learn, perform, and develop physically in the classroom environment. Self-efficacy influences the allocation of effort, willingness to repeat actions that were not performed successfully, persistence during task escalation, and interpretation of the mistakes made [1-5]. The teenage period is particularly sensitive due to possible doubts caused by visual competence differences and peer comparison. Self-efficacy might be developed through several mastery experiences where the learner realizes a mistake, makes the necessary changes to the way the movement is performed, and observes a positive change.

2.2. Artificial intelligence supported physical education

In AI-supported physical education, movement video footage is transformed into structured kinematics that could be analyzed during the process of practice. Markerless pose estimation is appropriate for school practice due to the lack of need for reflective markers, wearable devices, or laboratory cameras. Body landmarks could be used to express joint angles, segments positions, balance, and timing of the movement [6-8]. The challenge in the education process is to interpret the coordinates in terms of feedback that could be applied instantly by the adolescent. In this sense, automated feedback will be the most efficient when it highlights a few deviations that should be addressed and connected to the next attempt.

2.3. Feedback and mastery experience

Corrective feedback supports mastery by eliminating uncertainty between the execution and the required standard of the movement. Immediate feedback gives learners an opportunity to correlate an action with a particular change. In case the next action is done better, the change becomes a concrete mastery experience [9, 10]. Therefore, repetitive feedback to practice cycle might create a correlation between objective changes and self-efficacy beliefs. Such feedback should be accurate, immediate, and applicable in order to be valuable. In this regard, concise information related to the correctable elements of the movement might be more helpful than biomechanical data.

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3. Methodology

3.1. Participants and experimental design

Eighty-four students aged 13-15 from four physical education classes were assigned to either the AI supported or the traditional group with 42 students in each group based on the class. The intervention continued for eight weeks including two 40-minutes sessions a week. All participants practiced squats, forward lunges, and countermovement jumps in equal task order and practice quantity. Testing was done one week prior to the intervention and post-testing within three days after the last session. Display of AI was provided to participants of experimental group, groups were conducted separately, videos were coded anonymously. The same two teachers supervised both groups by using the same technical rubric.

3.2. AI supported feedback system

The feedback system was realized with Python 3.11 language in cooperation with MediaPipe Pose Landmarker and OpenCV. Video recordings were made with iPhone 15 in 1080p resolution and 30 frames/s from lateral-oblique position at the distance of 3.0 m from activity zone. Joint landmarks of the hip, knee, ankle, shoulder, and trunk with visibility less than 0.65 were not considered in the analysis. Trajectories of landmarks were filtered with the second-order Savitzky-Golay filter with seven frames window. Movements were segmented with knee flexion extrema and vertical displacement of hips. Joint angles were calculated using adjacent segments vector method. Reference distributions of joint angles were calculated as average angles, dispersion, and phase of movements from two certified teachers. Instead of calculation average difference between angles, the following score was used as shown in Equation (1):

$$S_{ir} = 100[1 - \frac{\sum_{j=1}^{J} w_j \bar{v}_{ijr} \psi(\frac{|\bar{\theta}_{ijr} - \mu_j|}{\sigma_j + \varepsilon})}{\sum_{j=1}^{J} w_j \bar{v}_{ijr}} - \lambda \frac{1}{T} \sum_{t=2}^{T} \left\| \Delta \boldsymbol{q}_{irt} - \Delta \boldsymbol{q}_t^{ref} \right\|_2]_0^1 \quad (1)$$

Where S_{ir} denotes the score for student i on repetition r, w_j is task-specific joint importance, $\bar{v}_{ijr}$ is mean landmark visibility, and μ_j and σ_j describe the teacher-derived reference distribution. Scores were rescaled to 0–100. The two largest weighted penalties generated concise corrective cues. A 60-video validation subset independently rated by both teachers yielded a mean joint-angle error of 3.78 ± 1.21° and ICC(2,1) = .914 between automated and expert scores. As shown in Figure 1, the AI-supported feedback mechanism integrates video capture, pose extraction, kinematic analysis, movement scoring, and immediate corrective feedback into a repeated practice cycle designed to enhance both movement performance and physical education self-efficacy.

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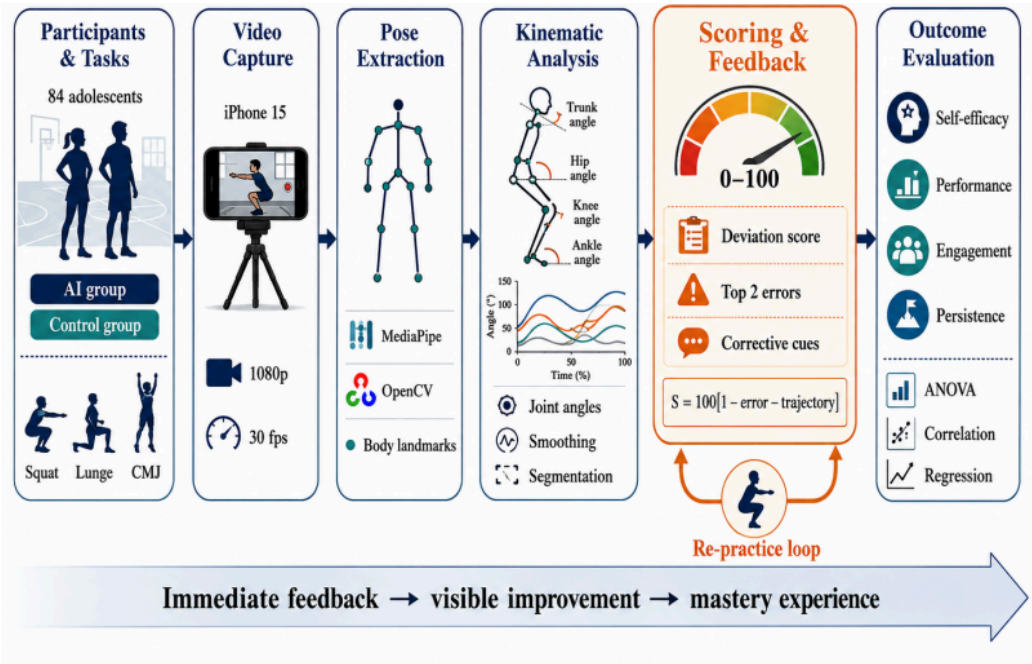

Figure 1. AI-supported feedback mechanism for enhancing physical education self-efficacy

3.3. Intervention procedure

Students performed five repetitions per movement each session that were recorded. Students in the AI condition saw a movement score, simplified skeleton model, and two corrective cues on an iPad Air immediately after each set. The feedback was visible for no more than 20 s before performing the next attempt and thus formed an attempt-diagnosis-correction-reattempt cycle. Further teacher corrections were used only if necessary for safety purposes. Students in the control condition performed the same number of repetitions and got verbal feedback from the same teachers based on the same criteria concerning joints and posture. Teachers provided no more than two corrective cues per set to equalize information bandwidth with the one in the AI condition. Exercise protocol, repetitions, session duration, and rest intervals were the same for both conditions.

3.4. Measures and data collection

Task-specific self-efficacy was measured with six seven-point items about learning, error correction, effort, task completion, and improvement. The internal consistency at the beginning of the study was $\alpha = .884$, and at post-test $\alpha = .903$. The movement performance measure was the AI-generated technical score out of 100. Videos of the control condition were processed only after collecting the data, so that the students did not get any automated scoring during the intervention. Feedback engagement in the AI condition comprised the number of screens with feedback seen before performing the next attempt and viewing duration normalized to 20 s per screen. Task persistence was operationally defined as extra repetitions in the last five minutes of each session. Logs of the system allowed tracking feedback engagement and persistence for each repetition.

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3.5. Statistical analysis

Statistical analyses were performed in IBM SPSS Statistics 29. Baseline equivalency was examined through independent-samples t-tests. Two 2 × 2 mixed-design ANOVAs were used to examine self-efficacy and movement performance with group as the between-subject variable and time as the within-subject variable. Interaction effects were reported as partial eta squared. Within-group changes were reported with Cohen's d. Correlations between improvements in movement, feedback engagement, persistence, and change in self-efficacy were examined with Pearson correlations. Among participants in the AI group, a hierarchical multiple regression analysis was used to predict post-intervention self-efficacy from baseline efficacy, movement score change, feedback engagement, and persistence. Residuals were tested for normality, homogeneity, and multicollinearity.

4. Results

4.1. Changes in physical education self-efficacy

Baseline self-efficacy did not differ between groups, $t(82) = -0.15$, $p = .882$. The AI group increased from 4.17 ± 0.62 to 5.39 ± 0.56***, whereas controls increased from 4.19 ± 0.60 to 4.66 ± 0.61**. The group × time interaction was significant, $F(1,82) = 42.31$, $p < .001$, $\eta p^2 = .340$. The within-group effect was larger for AI feedback, $d = 2.06$, than for conventional feedback, $d = 0.78$.

4.2. Movement performance and feedback engagement

Movement performance increased from 64.1 ± 6.8 to 82.3 ± 5.7*** in the AI group and from 64.5 ± 6.9 to 72.1 ± 6.4*** in controls, $F(1,82) = 58.74$, $p < .001$, $\eta p^2 = .417$. AI-group students reviewed 4.63 ± 0.29 of five available feedback screens per task block, with mean viewing duration of 14.8 ± 2.7 s. Voluntary repetitions increased from 2.71 ± 1.36 to 5.12 ± 1.74*** (see Table 1).

Table 1. Pre- and post-intervention outcomes

utcome	AI Group Pre	AI Group Post	Control Pre	Control Post	Group × Time
Self-efficacy	4.17 ± 0.62	5.39 ± 0.56***	4.19 ± 0.60	4.66 ± 0.61**	F = 42.31***
Movement score	64.1 ± 6.8	82.3 ± 5.7***	64.5 ± 6.9	72.1 ± 6.4***	F = 58.74***
Task persistence	2.71 ± 1.36	5.12 ± 1.74***	2.76 ± 1.31	3.48 ± 1.43*	F = 24.06***

Note. p < .05. ** p < .01. *** p < .001.

4.3. Relationship between AI feedback and self-efficacy improvement

Within the AI group, self-efficacy change correlated with movement-score improvement, $r = .61$***, feedback engagement, $r = .48$**, and task persistence, $r = .43$**. The final regression model explained 48.7% of adjusted variance in post-intervention self-efficacy, $F(4,37) = 10.74$, $p < .001$. Movement improvement was the strongest independent predictor, $\beta = .44$***, followed by feedback engagement, $\beta = .31$*, while task persistence showed a smaller contribution, $\beta = .19$. Visible technical progress was more strongly associated with efficacy gains than feedback exposure alone.

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5. Discussion

5.1. Impact of AI feedback on self-efficacy and technical skills

There is support for a mastery explanation because the intervention based on artificial intelligence generated greater effects on self-efficacy and movement execution. In the AI condition, students immediately got diagnosed, applied limited corrections, and noticed if their next try was better. Therefore, technical improvements became visible on each consecutive attempt. Movement execution correlated strongly with self-efficacy. However, the AI system did not make an attempt to improve confidence by general encouragement. Instead, efficacy beliefs grew along with the tangible improvements in the technical aspect. The engagement in the process added to the effect independently. Thus, AI feedback can be explained as the way of structuring mastery experience.

5.2. Implications and limitations of educational results

In usual classroom settings, one instructor cannot watch each repetition performed in class in a large group of students. Markerless pose recognition gives the chance to get individual information between the teacher's interventions. The two-cues design does not involve providing excessive biomechanical information. The responsibility for safety, exercise choice, motivation, and contextual interpretation stays with teachers, and AI helps with frequent kinematic comparison. Nevertheless, this research is limited by the single school, the use of only three structured movements and fixed camera position. The estimation of poses becomes less reliable in case of occlusion, rapid axial rotation, work with partners, and crowd activities. The system of scores depends on teacher-derived distributions and is not a universal biomechanical measure. More time is needed to find out how long self-efficacy benefits last without AI feedback.

6. Conclusion

AI-supported pose feedback improved movement execution and physical education self-efficacy of adolescents during an eight-week intervention. The main importance of the tool was that it created a quick mastery loop, in which students could find the technical mistake, apply the correction, and notice the change on their next attempt. The interaction and predictive effects suggest that the psychological benefits are directly connected to visible technical improvement. Therefore, markerless AI feedback can complement the instruction given by the teacher in case of concise, technically understandable, and frequent feedback.

References

[1] Jastrow, F., Greve, S., Thumel, M., Diekhoff, H., & Süßenbach, J. (2022). Digital technology in physical education: A systematic review of research from 2009 to 2020. *German Journal of Exercise and Sport Research, 52*(4), 504–528.

[2] Mödinger, M., Woll, A., & Wagner, I. (2022). Video-based visual feedback to enhance motor learning in physical education: A systematic review. *German Journal of Exercise and Sport Research, 52*(3), 447–460.

[3] Han, Y., Syed Ali, S. K. B., & Ji, L. (2022). Feedback for promoting motor skill learning in physical education: A trial sequential meta-analysis. *International Journal of Environmental Research and Public Health, 19*(22), 15361.

[4] Yu, H., van der Mars, H., Hastie, P. A., & Kulinna, P. H. (2022). Incorporating a motion analysis app in middle school badminton unit. *Journal of Teaching in Physical Education, 41*(4), 729–737.

[5] Hsu, W. T., Shang, I. W., Pan, Y. H., & Chou, C. C. (2023). Students' efficacy profiles and outcomes of perceived relation-inferred self-efficacy support in physical education. *International Journal of Sport and Exercise Psychology, 21*(1), 56–69.

DOI: 10.54254/2755-2721/2026.AST38040

[6] Hsia, L. H., Hwang, G. J., & Hwang, J. P. (2024). AI-facilitated reflective practice in physical education: An auto-assessment and feedback approach. *Interactive Learning Environments, 32*(9), 5267–5286.
[7] Sousa-Sá, E., Lander, N., Abu Alqumsan, A., Alsanwy, S., Nahavandi, D., Toomey, N., Mohamed, S., Lewis, S., & Barnett, L. M. (2024). Physical education teachers' perceptions of a motor competence assessment digital app. *Journal of Teaching in Physical Education, 43*(2), 276–291.
[8] Zhou, T., Wu, X., Wang, Y., Wang, Y., & Zhang, S. (2024). Application of artificial intelligence in physical education: A systematic review. *Education and Information Technologies, 29*(7), 8203–8220.
[9] Ma, J., Ma, L., Qi, S., Zhang, B., & Ruan, W. (2025). A practical study of artificial intelligence-based real-time feedback in online physical education teaching. *Smart Learning Environments, 12*, 52.
[10] Müller, J., & Wagner, I. (2026). Formative assessment of motor learning through digital tools in physical education: A systematic literature review. *European Physical Education Review, 32*(2), 383–403.