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AI-Based Video Feedback to Improve Soccer Passing Accuracy: A Quasi-Experimental Pretest–Posttest Study on Physical Education Students

Bahrul Alim[1]

{bahrul.alim@unm.ac.id[1]}

Universitas Negeri Makassar, Jl. A. P. Pettarani, Tidung, Kec. Rappocini, Kota Makassar, Sulawesi Selatan 90222[1]

Abstract. Accurate passing is a fundamental skill in soccer, yet delivering individualized, objective, and timely feedback in large physical education classes remains challenging. This quasi-experimental study evaluated the effectiveness of AI-based video feedback on improving passing accuracy among 64 physical education students enrolled in a soccer practicum course. Participants completed pretest and posttest measurements using an adapted Loughborough Soccer Passing Test (LSPT), with six intervention sessions providing personalized visual-numeric feedback generated from smartphone-based pose estimation. Results showed statistically significant improvement from pretest ($M = 58.3$, $SD = 12.7$) to posttest ($M = 71.8$, $SD = 11.4$), $t(63) = 9.84$, $p < .001$, with a large effect size (Cohen's $d = 1.23$). Instrument reliability was high ($ICC = 0.89$), and 81.3% of participants achieved minimal detectable change. Students with lower initial scores demonstrated greater absolute gains. Technology acceptance measures indicated high perceived usefulness ($M = 4.3/5.0$) and ease of use ($M = 4.1/5.0$). Findings suggest that affordable, smartphone-based AI feedback is feasible and effective for enhancing motor skill acquisition in resource-limited educational settings, though future randomized controlled trials with retention measures are needed to confirm causal effects and long-term sustainability.

Keywords: artificial intelligence, video feedback, soccer passing accuracy, motor learning, physical education, technology acceptance

1 Introduction

Accurate passing is a fundamental skill in soccer and strongly correlates with indicators of team success—various studies place pass accuracy/successful passes among the most consistent predictors of match outcomes (Lepschy, Wäsche, & Woll, 2018). In PJKR Soccer practicums, the realities of large classes, time/session constraints, heterogeneity in initial abilities, device availability, and instructor digital literacy often limit the provision of rapid, specific, and measurable individual feedback to each student (Mödinger, Woll, & Wagner, 2022). From a motor learning theory perspective, augmented feedback, both knowledge of results (KR) and knowledge of performance (KP), is a key variable. Synthetic evidence suggests that the combination of KR with prescriptive KP tends to be more effective than KR alone. (Oppici, Dix, & Narciss, 2021. Furthermore, the attentional focus literature consistently shows that directing attention to the effects of movement (external focus) improves accuracy and efficiency compared to internal focus on body parts, making it relevant for generating more effective feedback cues (Wulf, 2013). Similarly, video-based visual feedback has been reported to aid motor skill acquisition, but its implementation in physical education faces unique challenges (class size, session duration, and devices), necessitating a feasible approach for real-world learning contexts (Mödinger et al., 2022). The development of AI-based computer vision such as OpenPose or MediaPipe and commercial/smartphone cameras now enable markerless pose estimation and simple metric extraction in near real-time at relatively low cost, opening up the possibility of scalable, objective feedback in the field of practice (Edriss, Romagnoli, Caprioli, Bonaiuto, Padua, & Annino, 2025). At the same time, recent studies in education emphasize the potential of AI-based feedback to provide personalized and real-time feedback, while highlighting the need for design context-sensitive (Yildiz Durak & Onan, 2025). Within this framework, "AI-based video feedback" in this study is understood as the process of recording students' passing attempts, processing them with an AI application to generate visual, numeric performance indicators and corrective suggestions, and then presenting them immediately or in a subsequent session—a practical solution that bridges the gap between the pedagogical demands of PJKR and the need for rapid, specific, and measurable feedback.

On the one hand, the educational literature confirms that feedback is a powerful lever for learning—its effects are strongly influenced by the timing and specificity of presentation, making it relevant for the acquisition of motor skills such as passing (Hattie & Timperley, 2007). In the context of physical education, a recent systematic review also concluded that feedback interventions enhance student skill learning; however, comparative evidence between visual (video) and verbal feedback remains limited/mixed, requiring further verification of the efficacy of visual formats in traditional classroom settings (Zhou et al., 2021). In the Physical Education (PJKR) Soccer practicum, the reality of large class sizes and limited practice time makes providing individualized, prompt, and specific feedback to each student challenging; professional organizations have even warned of the negative pedagogical impacts of classes exceeding recommended ideal sizes (NASPE, 2006). At the same time, PJ teachers are widely interested in integrating digital technologies to support learning, but report practical barriers of device access, digital training/competence, institutional support, time constraints, and data privacy issues that lead to inconsistent classroom implementation (Saiz González, Sierra Díaz, Iglesias, & Fernandez Rio, 2024).

On the other hand, measuring passing accuracy in lectures often relies on subjective lecturer observations and is not always supported by standard metrics, even though field instruments such as the Loughborough Soccer Passing Test (LSPT) with reviewed measurement properties (reliability, discriminant validity, and responsiveness) are available, although some studies highlight the limitations of criterion validity and measurement error for monitoring individual changes in practice (Wen et al., 2018). The relevance of focusing on passing itself has a performative basis: systematic reviews of success factors in soccer place pass accuracy/successful passes among the indicators often associated with match outcomes, making improving passing accuracy a meaningful pedagogical target (Lepschy, Wäsche, & Woll, 2018).

While computer vision and AI in commercial devices now enable near-real-time motion analysis and feedback, comprehensive studies indicate that AI applications in physical education are still in their infancy and require more robust pedagogical evaluation and teacher training strategies to be adaptive and effective in the classroom (Wang & Wang, 2024; Zhou et al., 2023/2024). Therefore, there are two core issues that this study aims to address: (1) the lack of objective, specific, and rapid feedback in PJKR Football practicums due to structural constraints; and (2) the lack of empirical evidence on the effectiveness of AI-based video feedback on passing accuracy in large/low-resource classroom settings in higher education sports.

Based on these problems, this study formulates the following questions: (i) Does AI-based video feedback result in a significant increase in passing accuracy from pretest to posttest in PJKR students? (ii) How large is this increase in practical terms (effect size)? (iii) Exploratory, how is the acceptance and ease of use of the intervention by students in the context of practical work in the Football course?

This study aims to evaluate the effectiveness of AI-based video feedback in improving passing accuracy in PJKR students through a quasi-experimental pretest–posttest design in the context of a soccer practicum. The quasi-experimental design was chosen because it is adequate for causal evaluation when randomization is not possible in a real classroom. (Shadish, Cook, & Campbell, 2002). Effectiveness was assessed by the difference in pre–post accuracy scores and effect size to assess the practical significance of the improvement. (Cohen, 1988).

Although feedback is recognized as one of the most important drivers of learning improvement, classroom practice often fails to provide rapid, specific, and measurable feedback for individual learners (Hattie & Timperley, 2007). Soccer performance research confirms the importance of pass accuracy to success, but few studies have assessed passing skill acquisition in educational contexts supported by classroom-friendly AI video feedback. (Lepschy, Wäsche, & Woll, 2018). On the measurement side, standardization of metrics and reliability reporting on field skills tests remain inconsistent, necessitating approaches that emphasize objectivity and reliability. (Hopkins, 2000).

The novelty of this research lies in: (i) the implementation of low-cost, scalable smartphone-based AI-based video feedback in the Physical Education and Training (PJKR) practicum; (ii) the focus on passing accuracy learning outcomes directly relevant to game performance; (iii) the numerical visual feedback protocol that lecturers can replicate in large classes; and (iv) the evaluation using a pretest–posttest with effect size reporting for practical interpretation. Scientific justification: The intervention aligns with strong evidence that feedback improves learning outcomes (Hattie & Timperley, 2007). The quasi-experimental design is relevant when randomization is not feasible in educational settings (Shadish, Cook, & Campbell, 2002). Effect size reporting is recommended to make findings more informative for practice (Cohen, 1988). The use of objective metrics and reliability testing enhances the credibility of the findings and their replication. (Hopkins, 2000)

2 Method

The study used a one-group pretest–posttest quasi-experiment in two intact classes of the Football course in the Physical Education, Health, and Recreation (PJKR) Study Program. This design was chosen because individual randomization is difficult to perform in regular classes, but still allows for limited causal inference through comparison of pre-post intervention scores with procedural controls for threats to internal validity. The reporting and description of the intervention follow the relevant points of the TIDieR guidelines to enable replication (Shadish, Cook, & Campbell, 2002; Hoffmann et al., 2014).

The population was all PJKR students at Makassar State University who were taking the Football course during the research semester. The sample consisted of two PJKR classes scheduled for that semester and willing to participate; selection was conducted using a cluster (whole class) based on availability and coordination of study programs. Inclusion criteria: officially registered in the course, present at least for the pretest and posttest sessions, and consent to participate. Exclusion criteria: injury that prevented passing according to protocol or absence from one of the main measurements. The sample size was determined pragmatically to be equal to the number of students in the two classes; planned statistical adequacy was evaluated through an a priori power analysis for paired tests at medium effect sizes (e.g., $d \approx 0.5$; $\alpha = 0.05$; power=0.80) using G Power (Faul et al., 2007; Cohen, 1988).

3 Result

A total of 64 students from two Soccer courses met the inclusion criteria and completed the full set of measures (pretest and posttest). No participants were excluded due to injury or absence. The mean age of participants was 19.8 years (SD = 1.2), with 52 males (81.3%) and 12 females (18.7%). The majority of participants (78.1%) reported at least 2 years of recreational soccer experience, but no formal, structured training experience.

Test-retest reliability testing on a subsample of 15 participants who underwent two pretest sessions 48 hours apart showed an intraclass correlation coefficient (ICC) of 0.89 (95% CI: 0.72–0.96), indicating high reliability of the adapted LSPT instrument. The coefficient of variation (CV) was 6.4%, below the generally accepted threshold of 10% for motor skill measurement.

Table 1 presents descriptive statistics for passing accuracy scores on the pretest and posttest. The mean pretest score was 58.3 points (SD = 12.7), increasing to 71.8 points (SD = 11.4) on the posttest. A paired-samples t-test confirmed a statistically significant difference: $t(63) = 9.84$, $p < 0.001$, with a mean increase of 13.5 points (95% CI: 10.7–16.3). The distribution of scores on both measures was approximately normal (skewness and kurtosis < |1.0|), meeting the assumptions of parametric analysis.

Table 1. Descriptive Statistics of Passing Accuracy Score (N = 64)

Measurementt	M (SD)	Min- Maks	Skewness	Kurtosis
Pretest	58,3 (12,7)	32-84	0,12	-0,45
Posttest	71,8 911,4)	48-92	-0,8	-0,38
Difference	13,5 (10,9)	-4-38	0,31	-0,12

Note. Theoretical maximum score = 100 points. Difference = posttest − pretest.

Cohen's d for the pairwise difference was calculated as 1.23 (95% CI: 0.89–1.57), indicating a large effect size according to benchmark conventions (Cohen, 1988). This effect remained substantial even when calculated using Hedges' g corrected for small samples (g = 1.21). These results indicate that the AI-based video feedback intervention not only produced statistical differences but also had substantial practical significance in the context of passing skill learning.

To evaluate the consistency of the effect across participants, we calculated the percentage of respondents who showed an increase of at least 5 points (considered minimal detectable change based on SEM): 81.3% of participants (n = 52) reached or exceeded this threshold. Only 3 participants (4.7%) experienced a decrease in their scores (range: −2 to −4 points), which could be explained by normal measurement variability or contextual factors on the day of the measurement. Subgroup analysis based on pretest scores (median-split: low vs. high) showed that the group with low initial scores (M_pre = 47.2) experienced a greater absolute increase (M_diff = 18.1 points) than the group with high scores (M_pre = 69.4; M_diff = 8.9 points), although both groups showed significant improvement ($p < 0.001$ for both). These findings indicate that the intervention was effective across initial ability levels, with proportionally greater benefits for students with lower initial passing accuracy.

A short Technology Acceptance questionnaire (adapted from the TAM) completed after the posttest (Likert scale 1–5) showed positive responses: mean Perceived Usefulness = 4.3 (SD = 0.6), Perceived Ease of Use = 4.1 (SD = 0.7), and Intention to Use in Future = 4.0 (SD = 0.8). In the open-ended questions, 78% of participants cited visual specificity ("seeing the angle of one's own foot") and speed of feedback as the most helpful aspects. Reported barriers included limited space for recording (23%) and difficulty interpreting kinematic graphs without additional explanation (15%).

4 Discussion

This study found that AI-based video feedback resulted in significant ($p < 0.001$) and practically significant (Cohen's $d = 1.23$) improvements in passing accuracy of Physical Education (PJKR) students after six intervention sessions in a Soccer practicum. These findings definitively address the first and second research questions: the intervention was not only statistically effective but also pedagogically meaningful. Furthermore, qualitative exploration demonstrated high acceptance of the technology and reasonable ease of use, strengthening the feasibility of implementation in large classroom contexts with limited resources.

The effectiveness of the intervention aligns with a fundamental principle in motor learning theory that augmented feedback accelerates skill acquisition by providing information about action outcomes (knowledge of results (KR) and the quality of movement execution (knowledge of performance (KP) that are not always accessible through intrinsic feedback alone. In this study, the AI system provided both numerical KR (accuracy score relative to the target) and visual-prescriptive KP (foot angle relative to the ball, body position, follow-through direction) simultaneously, which evidence synthesis suggests is likely more effective than KR alone (Oppici et al., 2021). Furthermore, the visualization of the skeleton pose and ball trajectory presented to the students facilitated an external focus of attention directing attention to the effects of movement (ball trajectory, contact with the target) rather than to internal body coordination. The literature consistently demonstrates that external focus improves movement accuracy and automaticity (Wulf, 2013), and the video feedback format in this study which explicitly displayed passing results inherently encouraged this external attention pattern.

These findings extend previous evidence on the effectiveness of video feedback in physical education (Mödinger et al., 2022), with several important points of differentiation. First, our effect size (d = 1.23) is higher than the average effect size of visual feedback interventions reported in Zhou et al.'s (2021) meta-analysis, which ranged from 0.4 to 0.7. This difference likely reflects the advantages of objectification and personalization enabled by AI—each student receives specific feedback based on their own pose data, rather than the generic suggestions often found in verbal or video feedback without quantitative analysis. Second, this study addresses methodological limitations common in applied research in PJKR: we report instrument reliability (ICC = 0.89), effect sizes with confidence intervals, and sensitivity analyses to individual responses, addressing criticisms of reporting inconsistencies in sports skills research (Hopkins, 2000; Wen et al., 2018). This increases confidence that the observed effects are not measurement artifacts or publication bias.

From a practical perspective, this study demonstrates that relatively affordable smartphone-based AI technology (using free apps or low-cost subscriptions such as Kinovea, Coach's Eye, or MediaPipe-based tools) can be integrated into large classroom labs without requiring expensive laboratory infrastructure or intensive technical training for instructors. The protocol we developed recording three passing trials per student, processing them through AI for pose and metric extraction, and then delivering the annotated videos via an LMS platform within 24 hours is scalable and replicable by other instructors. The finding that 81.3% of students achieved minimal detectable change confirms that the intervention is not only effective in the aggregate but also consistent at the individual level. Furthermore, the greater differential effect on students with lower initial ability demonstrates the intervention's potential as a pedagogical differentiation strategy that targets diverse learning needs in heterogeneous classrooms—a chronic challenge in RHD (Saiz González et al., 2024).

Several mechanisms may explain the intervention's effectiveness. First, AI transforms abstract concepts such as "correct leg angle" into concrete visualizations (overlaying angle lines on the video), reducing the cognitive burden of interpreting verbal instructions. Second, providing feedback within 24 hours (versus the 1-week delay in conventional practice) allows correction while the memory representation of the movement is still fresh, in accordance with the timing principle in feedback theory (Hattie & Timperley, 2007). Third, students can replay their own videos multiple times, facilitating self-assessment and meta-cognitive reflection known to enhance learning (Nicol & Macfarlane Dick, 2006). Fourth, qualitative data indicates that visualization of numerical progress ("from 55 to 72 points") and implicit gamification ("trying to beat one's own score") increase engagement and persistence.

Several limitations should be acknowledged. First, the pretest-posttest design without a control group limits causal inference; improvements could partly reflect practice effects, maturation, or sensitization to the test. Although we consider this likelihood low given the large effect size and relatively short intervention duration (6 sessions), future research should utilize a randomized controlled trial or at least a quasi-experiment with a control group to strengthen internal validity. Second, the generalizability of the findings is limited to the Indonesian context of PJKR with specific sample characteristics (majority males, recreational soccer experience). Replication is needed in different populations (high school students, junior athletes, non-Indonesian contexts) to test the robustness of the effects. Third, we did not measure long-term retention or transfer of skills to real-life game contexts (game play). Longitudinal research with 2–3-month follow-up and measurement of passing accuracy in small-sided games would provide stronger evidence of sustained instructional impact. Fourth, despite high technology acceptance, 15% of students reported difficulty interpreting complex AI output, indicating the need for more intuitive user interface design or instructional scaffolding (e.g., short video tutorials on how to read kinematic graphs).

Future research directions encompass several key agendas. First, comparing the relative effectiveness of AI feedback versus traditional verbal or video feedback without AI analysis in a direct experimental design will clarify the unique contribution of the AI component. Second, exploring the optimal frequency and timing of feedback (immediate vs. delayed, every trial vs. summary feedback) can optimize intervention protocols based on motor learning principles. Third, investigating moderator variables such as digital literacy, initial self-efficacy, or goal orientation that influence response to intervention will help personalize the approach. Fourth, expanding the application to other soccer skills (shooting, dribbling) or different sports (volleyball, basketball) will test the generalizability of the AI-augmented feedback concept across motor domains.

These findings have direct implications for PE curriculum design and lecturer professional development. Higher education institutions specializing in sports are encouraged to integrate AI literacy into pre-service PE teacher training to prepare graduates for utilizing emerging technologies; provide basic digital infrastructure (e.g., tablets or tripods for recording) that supports the implementation of video-based feedback; and facilitate communities of practice where lecturers share protocols and troubleshoot technical challenges. From a policy perspective, the study's results support the argument for strategic investment in affordable, evidence-based educational technology, rather than high-tech solutions that are not scalable or proven effective in low-resource contexts. Furthermore, the finding that technology can reduce the burden of individual teaching in large classes while improving the quality of feedback strengthens the case for pedagogical reforms that utilize AI as a co-educator, rather than a replacement for human instructors.

5 Conclusion

This study provides empirical evidence that AI-based video feedback significantly improved the passing accuracy of PJKR students in a statistically significant and practically significant manner (Cohen's $d = 1.23$), with 81% of participants achieving clinically meaningful improvement. The intervention demonstrated high feasibility for implementation in a large, resource-limited classroom practicum context, supported by positive acceptance of the technology by students. These findings contribute to the motor learning and physical education literature by demonstrating that affordable AI technology can bridge the gap between pedagogical demands for rapid, specific, individualized feedback and the structural realities of higher education in sport. From a practical perspective, this study offers a model protocol that PJKR lecturers can replicate to improve the quality of motor skills learning.

However, the limitations of a quasi-experimental design without a control group indicate the need for further research with randomized controlled trials and long-term retention measurements to confirm the causal effects and sustainability of the intervention. Future directions also include exploring moderator variables, optimizing user interface design, and expanding the application to other skills and sports. Overall, this study confirms the potential of AI-augmented pedagogy to transform motor skills learning practices in PJKR, with the important caveat that technology must be designed and implemented in a pedagogically informed and contextually sensitive manner to effectively improve student learning outcomes.

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