

Computer vision feedback in physical education: Effects on motor performance, motivation, and movement error detection in long jump learning

EL AMARI MOHAMED¹, EL MOUTARAJI IMANE², ATIBI YASSINE³, EL MIR IMAN⁴

^{1,3} PhD Candidate; Computer, Networks, Mobility and Modeling Research Laboratory (IR2M), Faculty of Sciences and Techniques (FST), Hassan First University, Settat, MOROCCO

² Research Professor; Research Team in Sport Sciences, Sport Sciences Institute, Hassan First University of Settat, Settat, MOROCCO

⁴ Research Professor; Networks, Mobility and Modeling Research Laboratory (IR2M), Sport Sciences Institute, Hassan First University of Settat, Settat, MOROCCO

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Abstract:

Although advances in artificial intelligence (AI)-assisted feedback technology are spreading worldwide, empirical research on the effects of feedback on the motor learning process in educational contexts remains limited. Even fewer empirical studies have been performed in physical education and sports, where learners rely heavily on feedback from teachers and equipment to acquire psychomotor skills. This quasi-experimental study examines the effect of computer vision-based feedback on long jump learning among 87 Moroccan high school students. All participants were approximately 16.5 years old, and 53% were female. The experiment took place during physical education classes. The objective was to assess the impact of three forms of feedback (AI-based feedback delivered through computer vision technology, video feedback, and oral feedback) on performance, motivation, and error perception. Accordingly, 87 high school students were divided into three groups of 25, 29, and 33 learners, respectively, referred to as Groups 1, 2, and 3. Each group underwent a diagnostic test before four trials and, finally, a concluding evaluation test at the end of the experiment. Two psychological questionnaires were used to monitor the students' psychological progress in the experiment: the Exercise Motivation Scale-28 (EMS-28) and the Movement Specific Reinvestment Scale (MSRS), including the factors of conscious movement processing (CMP) and movement self-consciousness (MSC). Data analysis revealed highly significant differences among the three groups. Learners in Group 1 improved by approximately 21.5%. Their performance scores were significantly higher than those recorded for Groups 2 and 3 by approximately 9% and 7%, respectively. Learners using computer vision technology (Group 1) achieved the highest percentages on five motivational aspects and showed deeper insight into their mistakes compared with the other two groups. The scores for the CMP and MSC factors among learners in Group 1 also increased remarkably by approximately 16.7% and 30.8%, respectively, compared with the other two groups. The scores of the latter two groups remained almost unchanged. It can also be seen from the PCA plot (Figure 2) that there are high correlations among the variables (with r-values greater than 0.70) in Group 1. These results underscore the effectiveness of computer vision technology in improving the learning of physical education skills. The findings confirm that AI-assisted computer vision feedback is a powerful pedagogical tool in physical education, significantly improving motor performance, motivation, and error perception. This approach shows clear advantages over traditional feedback methods and emphasizes its strong potential for integration into modern educational practices.

Keywords: AI-assisted feedback; Motor learning; Biomechanical analysis; Intrinsic motivation; Movement self-consciousness; Augmented feedback

Introduction

Digital technologies are profoundly reshaping how the world teaches and learns. Their integration into education has been widely recognized as a key factor in improving learning outcomes, particularly in areas that require the acquisition of complex skills (Zhou et al., 2021). In physical education, where motor learning plays a central role, the use of technological tools has the potential to improve both performance and student engagement. Artificial intelligence technologies are increasingly being used to personalize learning processes by adapting instructional strategies to individual learner needs. Computer vision also contributes to more accurate analysis of athletic performance (Naik et al., 2022). In Morocco, the 2023–2026 Digital Transformation Plan aims to integrate new technologies into education (Tamer & Knidiri, 2023).

However, physical education and sports have largely remained outside this evolution. Feedback is an important pillar in the field of movement and motor learning. Recent research has shown that video feedback, for

example, significantly improves body awareness and the self-regulation of movements (Potdevin et al., 2013). This approach promotes a better understanding of movement patterns and supports error correction. At the same time, self-determination theory shows that intrinsic motivation is the primary driver of engagement (Ryan & Deci, 2000). Ultimately, learning progresses only through acquiring the ability to identify, perceive, and correct errors, which makes individuals more autonomous in the learning process. However, traditional feedback methods, which rely mainly on verbal instructions, often lack precision and immediacy, limiting their effectiveness in improving complex motor skills. A meta-analysis of 15 school-based PE studies confirmed that visual feedback modalities significantly improved motor skill learning, whereas verbal feedback alone produced no measurable changes (Han et al., 2022).

Although much is known about traditional video feedback, few studies have examined how computer vision can support schools (Koekoek et al., 2018). This technology enables automated and objective analysis of human movement in a short period without direct human intervention. It has the potential to improve the effectiveness of traditional visual feedback approaches (Möding et al., 2022). In addition, there is a lack of comparative studies examining different types of feedback—AI-based, video, and verbal—and their combined effects on motor performance, motivation, and error perception. Existing studies tend to isolate a single feedback modality, focus on laboratory or elite training settings, or overlook the psychological dimensions of learning, such as motivation and self-consciousness about movement (Zhou et al., 2021). To date, limited research has compared these methods to assess their effects on motor performance, motivation, and error perception in Morocco, particularly in school-based physical education contexts. A preliminary exploratory survey performed among 41 physical education teachers in the Settât region found that the vast majority considered verbal feedback alone inadequate for teaching complex motor skills and expressed a clear need to integrate visual and digital technologies into their teaching practices.

These gaps underscore the need for experimental studies performed in real educational settings to assess the effectiveness of emerging technologies in physical education.

The purpose of this study is to explain how three types of feedback—computer vision, delayed video, and traditional verbal feedback—influence long jump performance, motivation, and error perception in 87 Moroccan high school students. This work is based on three hypotheses: H1: Computer vision feedback will produce the greatest improvements in motor performance; H2: It will generate the highest levels of intrinsic motivation; and H3: It will result in superior error perception, reflected in greater gains in CMP and MSC scores on the MSRS.

Materials and methods

Participants

The study included 87 high school students (mean age: 16.5 ± 1.1 years) from the core curriculum of Allal Ben Abdellah High School in Settât City, Casablanca-Settât region, Morocco. The sample consisted of 54 girls (62.1%) and 33 boys (37.9%).

Participants were randomly assigned to three experimental groups: Group 1 (G1) received computer vision feedback ($n = 25$), Group 2 (G2) received delayed video feedback ($n = 29$), and Group 3 (G3) received traditional oral feedback ($n = 33$). Randomization was performed using a simple random allocation procedure to ensure equal distribution across groups.

Ethical approval for this study was granted by an institutional ethics board, and written informed consent was obtained from each student and their legal guardian.

Table I. Sample characteristics by group

Groups	Number	Girls	Boys	Mean age ($\pm$ SD)
G1 (computer vision)	25	16 (64%)	9 (36%)	16.4 ± 1.0
G2 (video feedback)	29	18 (62%)	11 (38%)	16.5 ± 1.2
G3 (oral feedback)	33	20 (61%)	13 (39%)	16.6 ± 1.1
Total	87	54 (62.1%)	33 (37.9%)	16.5 ± 1.1

Procedure

The experiment consisted of six sessions in total and was performed over three weeks. In the first session, participants completed an initial observation test (OT) and pre-training questionnaires. In the second through fifth sessions, participants experienced the lesson in the form of different types of feedback. In the sixth session, participants completed a final assessment test (AT) and end-of-training questionnaires. The biomechanical parameter used in the experiment was the angle of thigh extension in a cross position when the participant was in the take-off phase of the jump (Linthorne, 2005).

Testing protocol

Group 1: Using Python and MediaPipe (Lugaresi et al., 2019), an automated biomechanical analysis was performed through computer vision. The participant's 3D skeleton was visualized together with the thighs as two

green lines indicating the impulse angle. At the top of the video window, an angle indicator was also displayed in red for $<60^\circ$ (ineffective feedback), white for $60^\circ\text{--}90^\circ$ (effective feedback), and blue for $>90^\circ$ (optimal feedback). Video recordings were made using a camera set to 1080p resolution at 30 frames per second. The camera was placed approximately 2 m from the take-off board (He & Zhang, 2021) and directly faced the take-off area. Data were collected outdoors under typical physical education room conditions. Motion analysis was performed using the latest version of MediaPipe, and the take-off angle was calculated using a Python script that applied trigonometric functions based on hip and thigh coordinates (Cao et al., 2021).

Group 2: The participants' jumps were displayed on a computer screen.

Group 3: The teacher provided immediate feedback to the students through verbal instructions. The terrain, equipment, and timing were the same for all three groups.

Table II. Summary of feedback methods by group

Group	Method	Feedback type	Timing	Visual aid
G1	Computer vision	Automated biomechanical analysis	Immediate	3D skeleton + color coding
G2	Delayed video	Viewing with explanations	Delayed	Video recording
G3	Oral feedback	Verbal corrections	Immediate	None

Instruments

Motivation: Motivation was evaluated using the validated French version of the Sport Motivation Scale-28 (SMS-28). It enables the assessment of students' motivational profiles across seven dimensions based on responses provided on a 7-point Likert scale. The SMS-28 (Pelletier et al., 2019), a validated scale, considers the following intrinsic dimensions:

Intrinsic motivation: knowledge (IM-K), achievement (IM-A), feeling excitement (IM-S)

Extrinsic motivation: identified regulation (E-ID), introjected regulation (E-IJ), external regulation (E-ER)

Amotivation (AM)

Error Perception: The Movement-Specific Reinvestment Scale (MSRS) (Masters & Maxwell, 2008) is a tool that measures error perception across two subscales: conscious movement processing (CMP, 5 items) and movement self-consciousness (MSC, 5 items) using a 6-point Likert scale. For this study, it was necessary to translate the scale into French through a series of cross-cultural adaptation steps: forward translation, back translation, expert evaluation, and pilot testing with 15 students (Kinrade et al., 2015).

Motor performance: Long jump distance was measured in meters according to the 2007 Educational Guidelines for Physical Education in Morocco (Ministry of National Education of Morocco, 2007).

Data collection and analysis

Data for this study were collected in person during regular physical education classes. Questionnaires with inconsistent demographic information or with more than 20% missing data were excluded from the analysis. After data screening, a total of 87 valid questionnaires were retained for analysis. To assess the reliability of the data, Cronbach's alpha coefficients ranged from 0.78 to 0.91 across subscales.

Statistical analysis

Before proceeding with inferential statistical analysis, it was ensured that the necessary assumptions for performing parametric statistical tests were met. The normality of distribution for the data set was checked using the Shapiro–Wilk test, which showed that the data set was normally distributed ($p > 0.05$), thus satisfying a necessary condition for performing a parametric test. Homogeneity of variance was checked using Levene's test.

To assess differences between paired samples in the data set, a paired t-test was performed to compare pre-test and post-test results for each individual data set. To calculate effect size, Cohen's d was used for this test (Cohen, 2013).

To assess overall differences between groups, a one-way ANOVA was performed to compare post-test results for each data set. To calculate the effect size for this test (Sullivan & Feinn, 2012), eta squared (η^2) was used (Lakens, 2013). To assess overall differences between aggregated groups for different types of interventions, a principal component analysis (PCA) was performed using mean difference as the unit of analysis for each data set.

Varimax rotation was performed for this test (Abdi & Williams, 2010), and components with eigenvalues higher than 1 were retained. In this test, F1 accounted for 68.95% of the variance, and F2 accounted for 31.05%. Thus, together they accounted for 100% of the variance.

All statistical analyses were performed using Microsoft Excel, XLSTAT, and the Python programming language with the NumPy (Harris et al., 2020), SciPy (Virtanen et al., 2020), and Matplotlib (Hunter, 2007) libraries.

Results

Motor performance

Long jump performance improved significantly in each of the groups under investigation. Paired-samples t-tests showed significant increases in long jump distance from OT to AT in all groups (all $p < 0.001$; Table 3).

Table III. Performance evolution by group

Group	OT (m) Mean SD	AT (m) Mean SD	Progress (m)	Progress (%)	t	p	Cohen's d	95% CI (≈)
G1	3.42 0.68	4.16 0.72	+0.74	+21.5%	6.15	<0.001	1.06	[0.51–1.02]
G2	3.38 0.72	3.69 0.68	+0.31	+9.0%	2.58	<0.001	0.44	[0.19–0.43]
G3	3.25 0.65	3.48 0.70	+0.23	+7.0%	3.84	<0.001	0.34	[0.11–0.35]

Effect sizes were large for G1 ($d = 1.06$), moderate for G2 ($d = 0.44$), and small to moderate for G3 ($d = 0.34$). While Group 1 achieved an exceptional increase of 21.5%, it surpassed the improvement made by Group 2, which was 9.0%, and Group 3, whose increase was 7.0% (Wulf et al., 2010). The post-test results showed a significant difference between the experimental groups ($F(2,84) = 4.36$; $p = .016$), confirming the differential effect of feedback types. Post hoc pairwise comparisons (Tukey HSD) were then performed to identify which groups differed significantly. G1 showed the highest absolute and improvement test results (Chiviacowsky & Wulf, 2002). Figure 1 shows a comparison of the average performance of OT and AT across all three groups.

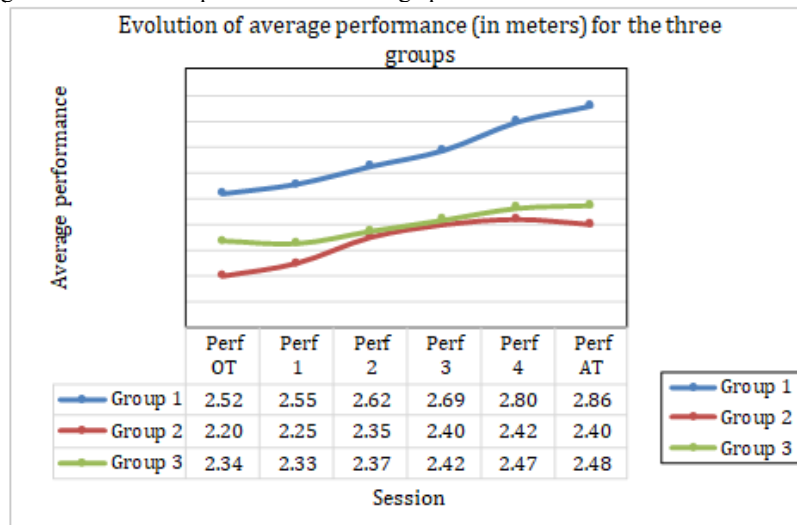


Figure I. Comparative trends in average performance (OT vs. AT)

Girls made significantly more progress than boys in every group, with Group 1 showing the largest difference. In this group, girls achieved 24% above the nationally expected levels, compared with 17.6% above those levels for boys.

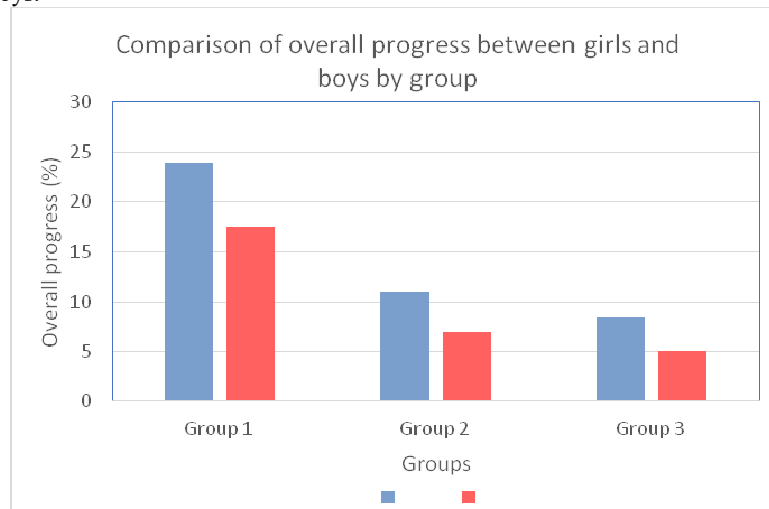


Figure II. Comparison of overall progress between girls and boys by group

Motivation (SMS-28)

Across six of the seven areas of the SMS-28, there has been a general increase in motivational scores, whereas AM has shown little change. G1 showed the largest percentage increases across most motivational dimensions, at 13.7%, particularly in the self-determined areas (Intrinsic Motivation – Stimulation (IM-S), which increased by 14.7%, and External Regulation – Identified (E-ID), which increased by 14.5%) (Deci et al., 1991).

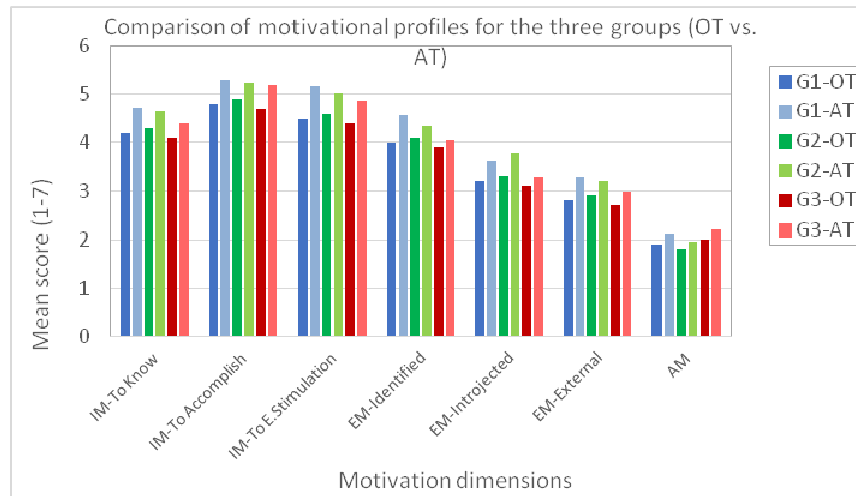
Following the post-test ANOVA, significant differences were found in Intrinsic Motivation – Knowledge (IM-K) ($F = 3.21$, $p = 0.045$), Intrinsic Motivation – Accomplish (IM-A) ($F = 4.07$, $p = 0.021$), and E-ID ($F = 4.53$, $p = 0.014$). Post hoc Tukey HSD comparisons indicated that G1 significantly outperformed G2 ($p = 0.032$) and G3 ($p = 0.008$), whereas G2 and G3 did not differ significantly ($p = 0.472$). The subscales are shown in Table 4.

Table IV. Average gains in motivational dimensions by group

Dimension	G1 (%)	G2 (%)	G3 (%)	F(2,84)	p	η ²	
IM-Knowledge		+12.6	+7.9	+7.3	3.21	0.045	0.071
IM-Accomplish	+10.0	+6.7	+10.2	4.07	0.021	0.088	
IM-Stimulation		+14.7	+8.9	+10.7	≈	≈	≈
EM-Identified		+14.5	+6.1	+4.1	4.53	0.014	0.097
EM-Introjected	+13.4	+14.2	+6.1	≈	≈	≈	
EM-External		+16.8	+10.7	+10.7	≈	≈	≈
Amotivation		+1.2	+0.8	+1.5	0.34	0.713	0.008

Between-group ANOVAs of post-test scores revealed significant differences in IM-K ($F(2,84) = 3.21$, $p = 0.045$, $\eta^2 = 0.071$), IM-A ($F(2,84) = 4.07$, $p = 0.021$, $\eta^2 = 0.088$), and E-ID ($F(2,84) = 4.53$, $p = 0.014$, $\eta^2 = 0.097$).

Figure 3 shows the mean SMS-28 motivational profiles at OT and AT for each group across the seven dimensions.

**Figure III.** Comparison of motivational profiles for the three groups (OT vs. AT)*Perception of errors (MSRS)*

G1 showed the greatest gains in both MSRS dimensions (MSC: +30.8%, CMP: +16.7%) compared to G3 (MSC: +3.8%, CMP: +4.3%). The MSRS scores for CMP and the MSC dimensions are presented in Table 5. The G1 and G2 groups showed significant improvement in both dimensions of error perception, whereas G3 showed only small improvements

Table V. Changes in MSRS scores by group

Group	CMP OT	CMP AT	Gain	t	p	d	MSC OT	MSC AT	Gain	t	p	d
G1	4.41	5.14	+0.73	4.82	<0.001	0.89	3.80	5.01	+1.21	6.95	<0.001	1.47
G2	4.32	4.90	+0.58	3.91	<0.001	0.76	3.86	4.41	+0.55	3.34	0.002	0.67
G3	4.14	4.32	+0.18	1.24	0.223	0.22	4.22	4.38	+0.16	0.98	0.335	0.17

Between-group ANOVAs revealed significant differences in CMP ($F(2,84) = 8.42, p < 0.001, \eta^2 = 0.167$) and MSC ($F(2,84) = 12.87, p < 0.001, \eta^2 = 0.234$). CMP and MSC scores between OT and AT at the observation level for all groups are compared in Figure 4.

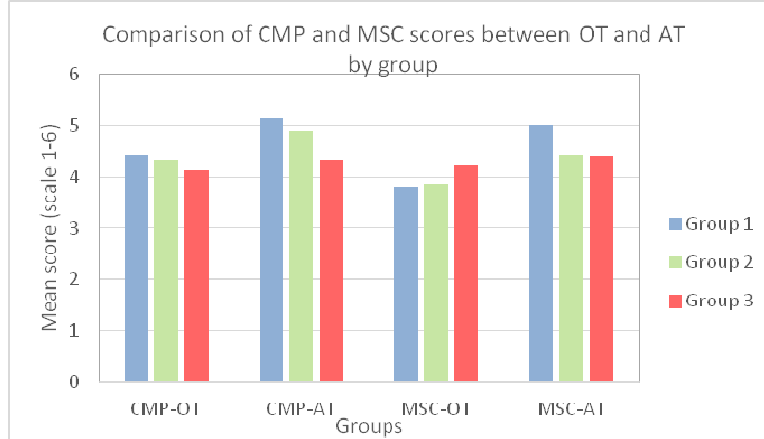


Figure IV. Mean CMP and MSC scores between OT and AT by group

The two MSRS measurements showed significant improvement across all test groups, with a considerable increase in the initial Group 1. The Computer Vision Group (G1) demonstrated the most significant enhancement, primarily in MSC. The subsequent groups showed lower values.

Group 1 (Computer Vision) showed a notable net increase, especially in the MSC dimension, with an increase of +1.21 points.

Group 2 (Video Feedback) showed moderate improvement in both aspects of the MSRS.

Group 3 (Oral Feedback) showed progress, although limited.

Multivariate analysis (PCA)

The results of the PCA indicated that the data set had a two-dimensional structure, which accounted for all the variance. This two-dimensional model consisted of two principal components. The first component accounted for 68.95% of the data and appeared to be related to self-determined and internalized motivation. The second component, which accounted for the remaining 31.05% of the data, was associated with Intrinsic Motivation - To Accomplish.

Table VI. Summary of the principal component analysis

Component	Eigenvalue	Variance (%)	Cumulative %
F1	6.21	68.95%	68.95%
F2	2.79	31.05%	100%

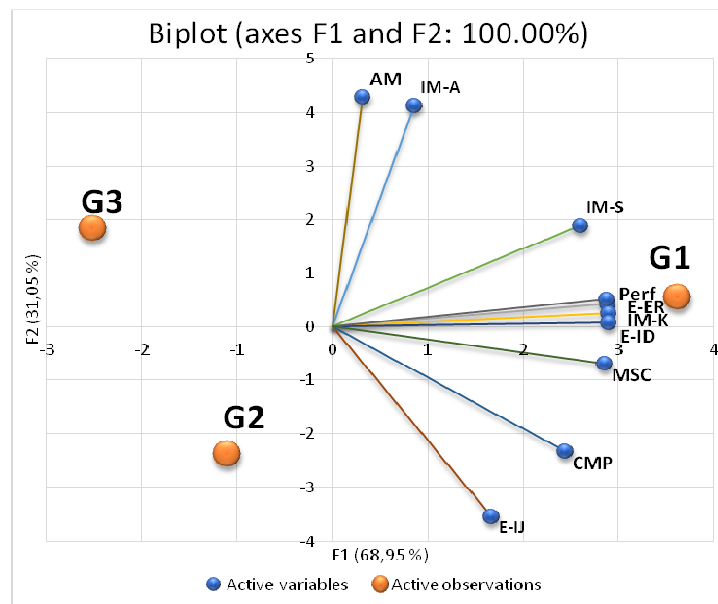


Figure V. Biplot: Projection of groups and variables onto F1 × F2

The PCA biplot (Figure 5) shows the relative positioning of the three groups and the contribution of each variable to the first two principal components (F1 and F2).

The first two components (F1: 68.95%, F2: 31.05%) account for all the variance. Visual inspection of the biplot suggests a stronger alignment between performance and psychological variables in G1 than in G2 and G3. This demonstrates the distinct impact of different feedback methods on learner performance and motivation.

Discussion

The purpose of this study was to examine the effects of three feedback modalities—computer vision feedback, delayed video feedback, and verbal feedback—on the performance, motivation, and error perception of Moroccan high school students in the long jump. The results showed that all feedback modalities improved performance; however, computer vision feedback produced greater gains in performance, motivation, and error perception than delayed video and verbal feedback. These findings build on previous research by confirming the effectiveness of AI-assisted feedback in real educational settings. Student engagement appeared to be influenced by both intrinsic motivation and the quality of feedback provided during the learning process. Students who received enhanced feedback showed larger increases in intrinsic and identified motivation (+14.7% and +14.5%), consistent with self-determination theory (Standage et al., 2005; Wininger, 2007). These findings align with studies suggesting that technology-supported feedback improves learners' sense of competence. Recent research also emphasizes that digital feedback environments foster engagement and autonomy in physical education (Sailer & Homner, 2020; Van Der Kleij et al., 2015).

Teachers can use computer vision as a pedagogical tool in long jump instruction. By analyzing key biomechanical parameters such as take-off angle and body alignment, they can provide immediate visual feedback after each attempt. This helps students better understand technical errors (Ntoumanis, 2001) and gradually improve movement execution. Such systems also promote autonomy because learners become more aware of their performance and actively participate in the correction process (Bandura, 1977). In addition, AI-based systems can support individualized feedback tailored to each learner's level (Zhai et al., 2021).

Error perception is a fundamental psychological component of motor learning. Group 1 demonstrated greater improvements in motor awareness (30.8%) than Groups 2 and 3 (14.2% and 3.8%). Previous research suggests that error perception helps sustain engagement in demanding physical activities (Kinrade et al., 2015). These results indicate that visual feedback increases awareness and supports more effective error correction (Wulf & Lewthwaite, 2016). This heightened awareness is also associated with improved self-regulation and decision-making during performance (Button et al., 2021).

Our findings support the three initial hypotheses. Group 1 achieved higher levels of intrinsic motivation than expected. Previous studies have shown that visual feedback enhances error detection and learning efficiency (Beilock & Carr, 2001). Likewise, the superiority of technology-based feedback over verbal feedback has been widely demonstrated. This can be explained by the ability of visual systems to provide accurate and immediate information (Tharatipyakul et al., 2024) about movement execution. Recent research also confirms that augmented feedback improves both skill acquisition and retention (Wulf & Lewthwaite, 2021).

However, this study has several limitations. The relatively small sample size and the specific educational context may limit the generalizability of the findings. Moreover, focusing on a single motor task (long jump) does not fully capture the diversity of physical education activities. Future research should investigate the use of AI-assisted feedback in other sports and educational settings, as well as its long-term effects. Despite these limitations, the findings provide strong evidence that AI-assisted feedback is a promising pedagogical tool for enhancing motor learning in real educational settings (Ma et al., 2025), with significant implications for physical education practice in Moroccan schools and beyond.

Conclusions

This study examined the effects of three feedback methods—computer vision, delayed video, and traditional verbal feedback—on long jump performance, motivation, and error perception among 87 Moroccan high school students. The results confirm the three initial hypotheses and demonstrate the greater effectiveness of computer vision feedback. Group 1 achieved significantly larger improvements: 21.5% in motor performance compared with 9.0% (G2) and 7.0% (G3), 13.7% in overall motivation, and 30.8% in motor self-awareness compared with 14.2% (G2) and 3.8% (G3). These findings provide strong empirical evidence that AI-assisted feedback improves both the motor and psychological dimensions of learning in physical education (Cavalcanti et al., 2021).

These results have important implications for teaching practices in physical education. Computer vision feedback provides immediate and objective biomechanical analysis, facilitating error detection, improving movement execution, and strengthening intrinsic motivation (Deci et al., 1999). This technology can be effectively integrated into Moroccan schools (Taam et al., 2023) as part of the 2023–2026 Digital Transformation Plan, providing teachers with an innovative and efficient tool to optimize skill acquisition and student engagement (Wang & Wang, 2024). More broadly, this study contributes to the growing body of research supporting the integration of intelligent technologies in educational settings (Gao, 2025). However, this

study has some limitations, including the short duration of the intervention and the relatively small sample size (three weeks, four sessions), as well as its focus on a single motor skill, the long jump, which may limit the generalizability of the findings. Future research should examine long-term retention effects through longitudinal studies and investigate the effectiveness of computer vision feedback across different motor skills and sports contexts in Moroccan educational settings (Guadagnoli & Lee, 2004).

Overall, this study highlights the potential of AI-assisted feedback as a transformative teaching approach in physical education. Its integration into school practices may help improve learning outcomes, foster student autonomy, and support the modernization of teaching methods in line with current educational reforms.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work, the author(s) used ChatGPT and Claude AI to assist with language refinement, including minor grammatical corrections, syntax improvement, and clarification of certain sentences.

After using these tools, the author(s) carefully reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Conflict of Interest

The authors declare no conflict of interest.

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