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Original Investigation

Animating Learning: Effects of AI-Based 3D Visual Feedback on Tackling Skill Acquisition, Motivation, and Performance in Youth Soccer

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Purpose: The integration of visual feedback (VFB) has become essential in physical education (PE), particularly with the emergence in artificial intelligence (AI) technologies. However, tackling techniques in youth soccer training have received limited empirical attention, even though they represent a complex and high-risk defensive skill. The purpose of the study was to analyse the effects of AI-enhanced VFB, using 3D animated motion capture, on the acquisition of tackling skills among youth soccer players.
Methods: Twenty-three participants were randomly assigned to an experimental group (EG; n = 12), utilizing AI-animated VFB, or to a control group (CG; n = 11) which received only verbal feedback. Technical performance was evaluated through four validated success criteria at the 1st, 6th, and 12th training lessons, while biomechanical efficiency was measured by comparing the trunk-leg angle to a model angle (167.3°). Motivation was evaluated using the Situational Motivation Scale.
Results: The findings show that the EG achieved a significantly greater improvement in technical performance (+179%) compared to the CG (+96%), with very marked effects for leg-knee positioning (Criteria 3) and ball contact (Criteria 4). The leg-trunk angle of the EG also improved significantly (+23.84%), approaching the expert model, while the CG showed only a modest increase (+9.63%). Furthermore, intrinsic motivation increased significantly in the EG ($P = .001$; d = 1.44), accompanied by a significant reduction in amotivation ($P = .004$; d = 1.07).
Conclusions: The AI-enhanced VFB allowed players to analyse their performance through 3D animations, facilitating skill improvement. These findings highlight the potential of AI-driven visual feedback in sports training, through further research needed to optimize its application in skill acquisition.

Keywords: Artificial intelligence; Visual Feedback; Motor Learning; Soccer; Tackling; Motivation.

Introduction

The development of the Information and communication technology (ICT) have influenced modern life by introducing advanced methods across fields. In particular, the education field has experienced considerable improvement through the use of ICT which plays a crucial role in school programs [1,2]. In addition, the implementation of artificial intelligence in education (AIED) increased in recent years due to the rise of big data. This growth has enhanced data analytics capabilities, enabling the customization of the learning models and thereby improving educational outcomes [3,4]. From this perspective, AI's role extends to various types of analyses which facilitate teaching methods, optimize training processes, and provide personalized insights based on learner Data [5]. AI powered systems represent innovative technologies that increasingly operate autonomously, using advanced algorithms to shape and develop learners' skills [6], while also helping to reduce injuries through predictive analysis and real-time monitoring of physiological and biomechanical data [7].

The physical activity domain is continuously evolving through scientific research focused on training interventions aimed at optimizing athletic performance [8]. The development of human intelligence and motor skills relies on various theoretical frameworks and methodological approaches [9]. Innovations in physical education (PE) facilitate the incorporation of AI into teaching methodologies, providing educators with adaptive tools that create engaging learning experiences for students [10,11]. This have even contributed to notable advancements in both sports training and athletic performance [12]. The AI integration into this process has the potential to enhance outcomes significantly [13,14]. In this context, motion capture technology is increasingly utilized to analyze and enhance sports performance [15,16]. Furthermore, the categorization of this technology has different types as the cinematography capture [16], the electromagnetic capture system or the computer vision capture (2D or 3D) in a single person and for multi-person which its verified in different physical activities [17].

In the teaching and learning process, feedback mechanisms provide corrective information and support student learning [18–22]. Visual feedback has been shown to be effective over short or long intervention periods [23,24], contributing to an enhanced pedagogical environment [25].

In soccer [26–28], researchers demonstrated that emerging technologies in professional leagues enhance the accuracy and breadth of player data collection. AI significantly advances data analysis through diverse tools and platforms, such as the 2022 World Cup data app, which delivers real-time player statistics to spectators in the stadium [29]. Furthermore, AI technology has been integrated into youth training programs to enhance the development of tactical and technical skills [30,31]. Among defensive skills in soccer, tackling is considered one of the most complex techniques, designed to dispossess the attacker and regain control of the ball [32,33]. There are various types and methods of tackling, each serving different tactical purposes ranging from simply stopping the opponent's advance to winning the ball and initiating a counterattack [34]. Some researchers, such as [35] have emphasized that both the player executing the tackle and the player being tackled face an increased risk of injury. This finding underscores the significant physical intensity and biomechanical complexity involved in these interactions, highlighting the need to reinforce injury prevention strategies. Consequently, integrating biomechanical analysis and targeted training protocols can help reduce injury incidence while optimizing performance and safety in tackling situations [36].

The introduction of new technology models has a positively influenced student motivation, playing a crucial role in enhancing engagement and performance outcomes. Pedagogical tools in PE are designed to create a supportive learning environment that fosters motor skill development and sustained interest [25]. Educators are responsible for selecting appropriately challenging tasks that promote both extrinsic and intrinsic motivation. The integration of the visual feedback enhances the student's autonomy and self-regulation, thereby increasing motivation and engagement in PE [37]. Strategies such as goal setting, positive reinforcement, and game-based learning significantly contribute to student involvement. Additionally, motivation shaped by students' prior experiences and personal interest in sports. Therefore, a well-structured pedagogical approach is essential for maximizing motivation and educational outcomes. Supporting this, [38] emphasize that physical contact, such as tackling, is a fundamental aspect of youth soccer practice but carries an elevated risk of injury, particularly concussion. They suggest that effective communication between coaches and athletes regarding safe engagement in contact can serve as a preventive strategy. In line with these insights, the present study aims to analyse tackling techniques to young footballers. Using real-time motion capture, this study seeks to evaluate how this technology can optimize teaching and learning processes in physical education by facilitating postural analysis, improving understanding of technical efficiency, and promoting the development of safe motor skills.

Methods

Participant

Twenty-three male soccer players were recruited from a local soccer team (Age 16.10±.40 years, body mass 60.70±4.50 kg, stature 181.30±6.00 cm, BMI: 18.61±.60 $kg \cdot m^{-2}$). Eligibility for participation in this study required that each participant have at least three years of football experience with their local team and have not suffered any lower-body injuries in the previous six months. Participants who did not meet these criteria were excluded from the study. They were divided into two groups: an experimental group (EG) of 12 players who received video feedback in the form of animated 3D visuals of their actions, and a control group (CG) of 11 players who received only verbal feedback (Figure 1).

Two experienced CAF-B-certified coaches conducted the training sessions. The study protocol was approved by the local research ethics committee (N: UR18JS01). Informed consent was obtained from all players and their families for participation in the study and for the use of 3D animation videos during training sessions to assess their impact on learning outcomes.

Experimental design

Over a six-week period, participants engaged in a standardized training program consisting of two sessions per week with 90 minutes for each. During these sessions, both groups trained together and performed identical warm-up routines. The FIFA 11+ warm-up program, developed by the 'Fédération Internationale de Football Association' (FIFA), is specifically designed to reduce injury risk and enhance key physical attributes in athletes, such as strength, agility, balance, and flexibility. The program comprises a structured, 20-minute warm-up routine divided into three distinct sections: initial running exercises, core and leg strengthening with plyometric components, and concluding zigzag runs with rapid directional changes [39,40]. The training program, developed by the English Football Association, offers a series of progressive teaching situations. The approach increases in intensity and complexity: it begins with simple drills (1 vs. 0), progresses to individual duels (1 vs. 1), and then to numerical superiority situations (2 vs. 1) which replicate real match conditions and enhance task difficulty and tackling efficiency.

The training focused on slide tackle objectives tailored to the study population [34] and aimed to enhance tackling techniques in football, specifically targeting the effective interception of the ball. The two coaches give an oral presentation about the situation with the understanding of the players. Each participant in both groups was required to repeat the tackling action four times. On the fif[th] repetition, they awaited the coach's signal, which served as a trigger for the camera to capture their performance for subsequent analysis. Participants in the EG watched videos of their own tackling actions alongside animated 3D models of those actions on the same screen. In contrast, participants in the CG had their actions recorded by the coach but did not see any video footage; instead, they received only verbal feedback from the coach.

Anthropometric measurement

Anthropometric measures were taken with light clothing and no shoes for the subjects using a bioelectrical impedance scale (TBF-300, Tanita, Tokyo, Japan). In this intervention, a camera (30 FPS) was mounted on a tripod to ensure stable video capture (NIKON Coolpix 500, Ayutthaya, Thailand). The recorded videos were organized by group and subsequently transferred to a laptop via a micro-SD card [25]. Using the AI software 'DEEPMOTION' (DeepMotion, San Francisco, USA), video were converted into 3D animations [41] through a motion-capture and physics-based animation system. Its core functionality relies on a multistage pipeline of advanced Deep Learning algorithms that identify and

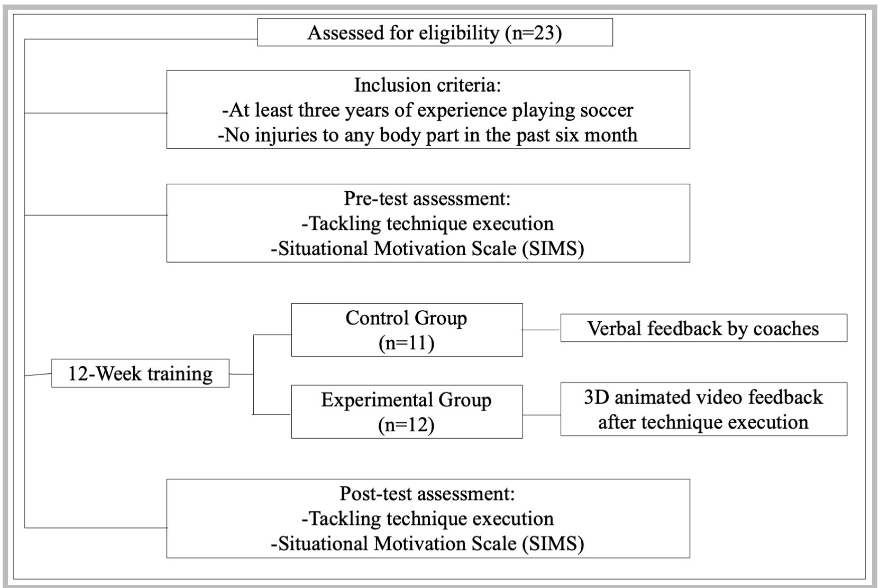

Figure 1. Flowchart of the study intervention.

track human joint positions, reconstruct full-body movements, and ensure biomechanically plausible avatar dynamics. The AI and Machine Learning components are therefore indispensable for non-invasive extraction, reconstruction, and refinement of accurate, high-fidelity 3D motion data. Movements are captured from uploaded videos or sensor-based inputs and subsequently processed through physics simulations to enhance clarity and realism (Figure 2 A, B, C).

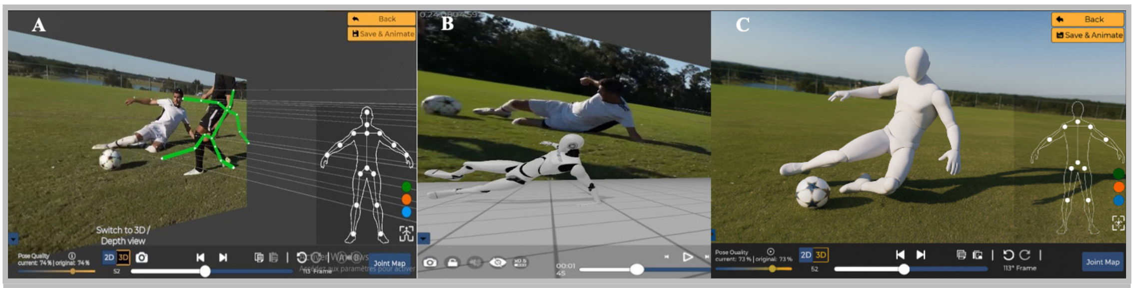

Figure 2. Conversion of a video into 3D animation using DeepMotion Animate 3D, (A) Joint detection and 2D skeleted extraction from original video ; (B) superimposition of the 3D skeleton onto the video for kinematic validation; (C) generation of a realistic animated avatar based on motion data using DeepMotion© software.

Data Collection

After collecting the relevant video sequences, the DEEPMOTION platform was used to transform players' actions into animated 3D visualizations. Tackling motor performance was then assessed using two complementary methods. First, a structured observation grid was developed based on four fundamental technical criteria: (C1) lateral glide, (C2) maintenance of balance, (C3) correct positioning of the leg and knee behind the ball, and (C4) ball contact, as described by [34]. This grid was applied during the video analyses of the 1st, 6th, and 12th training sessions. Each player's performance was rated on a 5-point scale for each criterion, ranging from 0 (----, null performance) to 4 (++++, excellent performance). Performance coding was independently conducted by two FIFA experts, both international trainers and assessors, thereby ensuring the validity of the assessment. Inter-coder reliability, calculated by the ICC (bidirectional random effects model), exceeded .80, indicating satisfactory reliability. Second, a reference model was created using software that analyzed online video footage of professional Premier League players (2023/2024 season; Manchester City vs. Arsenal) performing the tackle with optimal technique.

Deep Motion was used to decompose and faithfully reproduce the players' technical gestures in 3D environment, providing a relevant visual support. Using this 3D model (Figure 3), a reference was accurately measured with Kinovea software ($X = 167.3°$). This value served as a quantitative criterion for evaluating successful gesture execution (Kinovea, Lasne, Brabant Wallon, Belgium).

In addition, to assess the intervention's effect on player motivation, the Situational Motivation Scale (SIMS) developed by [42] was administered during both the first and final sessions. This instrument measures three dimensions of motivation across 16 items: intrinsic, extrinsic (identified and external regulation), and amotivation. Items are scored on a 7-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree).

Statistical Analysis

Data were presented as arithmetic means and standard deviation (mean ±SD). Descriptive statistical analyses were conducted using the IBM SPSS Statistics 27.0.1 (IBM SPSS Inc, New York, USA) for both video feedback group (EG), and the verbal feedback groups (CG). The normality was verified using the shapiro wilk's test. When normality was verified, a two-way mixed design ANOVA (2 groups: CG vs EG × 2 time points: pre-test and post-test) with repeated measures on the time factor was conducted to assess players' tackling performance scores and trunk-leg angle variations over time. The sphericity assumption for ANOVA was assessed using Mauchly's test. If violated ($p < .05$), a Greenhouse-Geisser correction was applied when Epsilon was <.75, and a Huynh-Feldt correction when Epsilon was >.75. The fisher value (F) were reported to reflect the variance between the groups mean. The evolution rate's percentage (Δ%) and effect size (ES) were measured. Effect size was interpreted

Figure 3. 3D model illustrating the reference angle of optimal tackling technique.

as follows: ES <.20 = small; .40<ES<.60 = moderate; and ES >.70 = large. An analysis of standardized effect size (Cohen's d) was conducted to evaluate the magnitude of differences between variables, with effects classified into the following ranges: ≤.20 (trivial), ≤.60 (small), ≤1.20 (moderate), ≤2.0 (large), ≤4.0 (very large), and >4.0 (extremely large) [43].

Results

Technical scores

Figure (4A) shows the tackling performance scores recorded for the video feedback group (EG), and the verbal feedback groups (CG) during the 1st (T0), 6th (T1) and 12th (T2) lessons and the

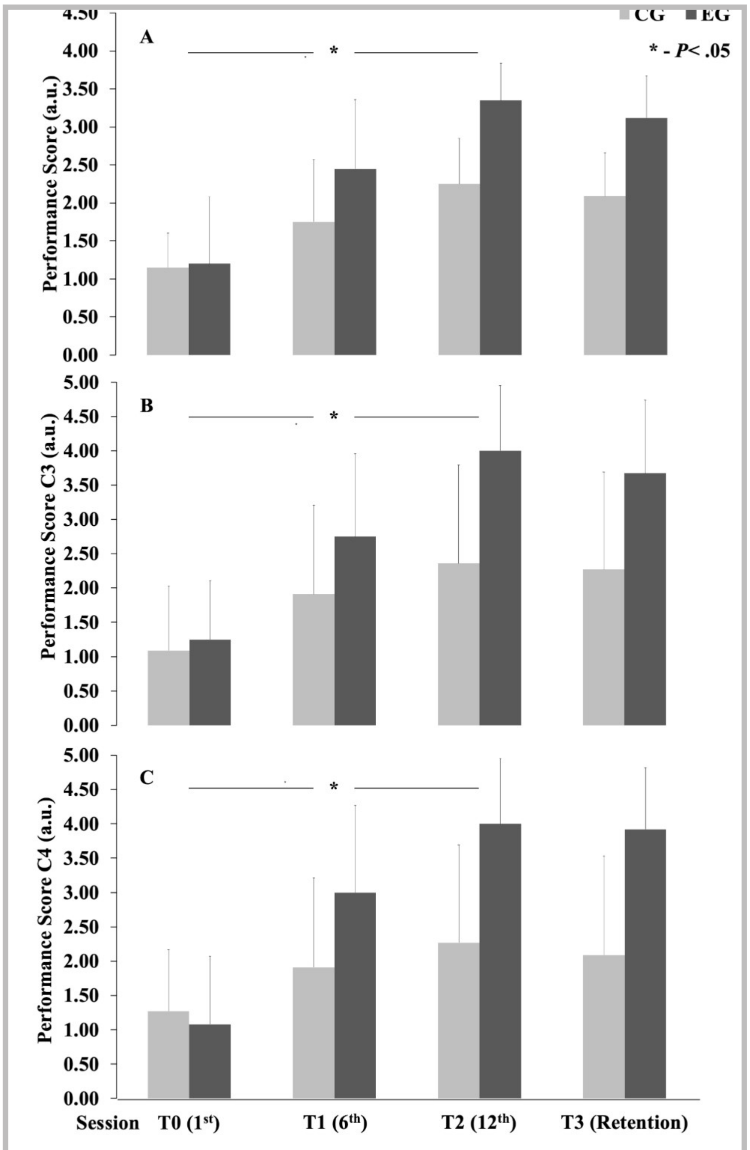

Figure 4. Performance scores (A), performance score C3 (B), performance score C4 (C) in EG (video feedback) vs CG (verbal feedback) over sessions T0-T3.

retention phase (T3). These scores were calculated as the sum of the scores obtained for the four technical success criteria (Total Scores = C1+C2+C3+C4), providing an overall assessment of tackling technique performance. At baseline (before intervention, 1st), no significant differences were detected between the EG and the CG, indicating that both groups were comparable prior to the intervention.

The results of a repeated measures ANOVA showed significant intervention effects (group × time), in the EG compared to the CG (F=3.37; P= .044; ES=.138) with a strong effect of time on performance (P= .000; ES=.598) implying a significant improvement over the course of the intervention regardless of the group.

Between time T0 and T2 (duration of experimental intervention), post hoc analysis indicated that tackling performance scores were significantly higher in the EG than in the CG. The performance increased in the EG, by 179% (t=-7.633; P=.000<.001; d=2.20) indicating a very large effect size. In the CG the performance improved by 96% (t=-4.707; P=.001; d=1.42 [large effect size]).

In a second step, statistical analyses were conducted on each of the technical criteria individually, in order to refine the interpretation of the overall results and better understand the specific evolution of each component of tackling performance. A repeated measure ANOVA was conducted to analyse the evolution of scores to the four technical success criterion (C1 to C4) for the EG, and the CG during the 1st (T0), 6th (T1) and 12th (T2) lessons and the retention phase (T3). Results showed no significant group × time interaction for C1 and C2 (F= .069; P=.884 and F= .33; P=.719, respectively), indicating that both groups improved similarly across sessions. In contrast, the statistical analysis revealed a significant group × time interaction for C3 (F= 3.95; P=.027, ES= .158) indicating a moderate interaction effect as shown in Figure 4B, and for C4 (F= 4.33; P=.019, ES= .171 [moderate effect]) as shown in Figure 4C. Post hoc analyses showed a significant improvement following intervention (T0 to T2) in the E, for both C3 (Δ= 220%; t=-7.396; P=.000<.001; d=2.14) and C4 (Δ= 270%; t=-7.00; P=.000<.001; d=2.021), each indicating a very large effect size.

Trunk leg angle results

The statistical analysis with a repeated measures ANOVA (group × time) in Table 1 showed a significant interaction effect on leg-trunk angle ($F_{(1,21)}$ = 18.19; P= .001; ES = .464), indicating a differentiated evolution between groups over time. Post hoc analyses showed a significant improvement in leg-trunk angle for the EG (Δ= 23.84%; t=-6.047; P=.000<.001; d=1.75), indicating a large effect size. In contrast, the CG, which received verbal feedback, showed only a modest and non-significant improvement (Δ= 9.63%). The post-test trunk-leg angle values in the EG were closer to the predefined performance criteria (167.3°), indicating improvement motor learning and a better level of technical in the tackling technique.

Table 1. Effects of video feedback (vs verbal feedback) on changes in trunk-leg in soccer tackling technique over 12 weeks.

Variable	EG (*n*=12)		CG (*n*=11)		ANOVA (group × time)		
	Pre	Post	Pre	Post	F	*P*	ES
Trunk leg angle (°)	112.16 ±15.03	145.9±14.53*	110.18±16.76	120.54±11.94	18.189	.025	.218

Note: EG = video feedback group; CG = verbal group; "*" – P< .05 between lesson 1 and lesson 12 for the same group; F= Test value; ES = effect size.

Motivation scores

Table 2 presents the results of comparing the two groups using repeated measures ANOVA for each SIMS motivation subscale for both groups between the 1st and 12th sessions. The results showed significant interaction effects (group × time) for intrinsic motivation (F= 16.48; P=.001) indicating a large effect (ES=.440), and for amotivation (F= 5.25; P=.032) indicating a moderate effect (ES=.2). However, no significant group × time interaction was observed for Identified regulation and External regulation (F= 3.35; P=.081 and F= 8.61; P=.266, respectively).

Table 2. Changes in motivation scores between lessons 1 (pre-test) and 12 (post-test).

SIMS	EG (*n*=12)		CG (*n*=11)		ANOVA (group × time)		
	Pre	Post	Pre	Post	F	*P*	ES
Intrinsic Motivation (a.u.)	3.50±0.98	5.94±0.98*	3.69±0.60	3.96±0.72	16.48	.001	.440
Identified regulation (a.u.)	4.52±0.78	4.94±0.64	4.75±0.79	4.39±0.49	3.35	.081	.138
External Regulation (a.u.)	4.00±0.87	5.08±0.66	4.18±0.83	4.66±0.96	8.61	.266	.059
Amotivation (a.u.)	3.25±0.74	2.22±0.79*	2.95±0.69	3.02±0.91	5.256	.032	.200

Note: Values (scores 7-point Likert scale) are presented as Mean ± SD. SIMS = Situational Motivation Scale. EG = video feedback group; CG = verbal group. "*" – P< .05 difference between lesson 1 and lesson 12 for the same group; F= Test value; ES = effect size.

Post hoc analysis using a paired t-test confirmed a significant increase in intrinsic motivation (t=-4.994; P=.000<.001; d=1.44) as well as a significant reduction in amotivation (t=3.698; P=.004<.001; d=1.07) after the VFB intervention in the EG.

Discussion

This study aimed to evaluate AI-based animated video feedback technology, using DeepMotion Animate 3D, as a tool to improve the learning of tackling techniques in young football players. The study focused on three main criteria: technical performance, biomechanical variables (including trunk-leg angle), and situational motivation. The results demonstrated a significant advantage of the video-based feedback (VFB) approach over verbal feedback on all measured dimensions, confirming the pedagogical effectiveness of this technology for mastering

complex and high-risk technical skills.
Result analysis showed that while performance scores improved moderately between the first and sixth sessions, a more substantial enhancement was observed by the twelfth session. One of the main findings concerns the significant improvement in overall technical performance observed in the experimental group (EG), with an increase of 179% between the first and twelfth sessions, compared to 96% in the control group (CG). However, when considering each criterion individually, the EG showed a significant greater progress than the CG, particularly on C3 (220% EG vs. 116% CG: correct positioning of the leg and knee behind the ball) and C4 (270% EG vs. 79% CG: contacting the ball). Specifically, the experimental group (EG) significantly outperformed the control group (CG), demonstrating a substantial improvement with a very large effect size (d = 2.021). These results confirm the positive impact of video feedback (VFB) on motor learning and are consistent with previous research [44], which identifies ball contact (C4) as the most accessible phase, both perceptually and motorically.
This discrepancy may be explained by the fact that, as noted by [33], “side sliding” and “maintaining balance” are more difficult to acquire and master. These are sequential and complex motor skills that require prolonged practice and coordination. Side sliding is considered the most complex element to teach due to the need for precise timing, body control, and risk management [33]. Furthermore, maintaining balance requires precise muscle activation and well-developed spatial awareness, which are essential for the effective and safe execution of tackling techniques [44].
From a biomechanical perspective on soccer tackle analysis, [33] highlighted the importance of considering the trunk-leg joint angle as one of the fundamental principles of technical execution. Our statistical analysis finding revealed that post intervention values approached the reference angle (167.3°) significantly more closely, with an improvement of 23.84% in the EG (EG; d = 1.75) compared to only 9.63% in the CG. These finding confirm the role of VFB AI-based animation in enhancing body awareness and motor control [41,45].
Additionally, these improvement reflects a high level of precision, execution and the use of sensory feedback, which are key to safely regaining possession while minimizing contact and injury risk [33,38]. The integration of motion capture and advanced technology into the training process served as an innovative form of visual feedback, significantly improving motor skill acquisition and learning outcomes. Visual feedback models, such as mirror feedback and VFB [45], enhance motor learning by improving real-time performance visualizations that refine movement execution and accelerate skill acquisition. Previous research has highlighted the significance of AI and machine learning in soccer, particularly for tactical knowledge [46], technical skill development [47], and adaptation to individual learning styles [48].
The present study, shows that the integration of the DeepMotion AI-based platform enabled the EG to significantly improve their motor performance. The innovative contribution of this strategy lies in its ability to provide youth players with 360-degree visualization of their actions, improving their understanding of body positioning and movement patterns. These finding constitute an original contribution to the analysis of tackling techniques and confirm the potential of AI technologies to optimize motor learning, in line with recent research [12,14].
Consistent with these findings, this study highlights the crucial role of tackling as both a defensive and transitional technique in football. By limiting the opponent's attacking opportunities and facilitating counterattacks, tackling appears to be a key action in one-on-one situations. In this context, some sports organizations emphasize teaching tackling skills across all age groups and skill levels example: English Football Association. They view tackling as a foundational defensive technique crucial for both disrupting offensive plays and initiating counterattacks. Therefore, enhancing motor learning of tackling through AI-based feedback not only improves defensive effectiveness but also contributes to overall team performance and strategic success [27,32,49].
In terms of motivational profile, the results indicate that motivational development within the experimental group (EG) significantly improved young players' intrinsic enjoyment. This increase in intrinsic motivation, in turn, had a substantial positive effect on their learning performance. Consistent with previous research [25,50,51], the video-based feedback (VFB) intervention resulted in a significant increase in intrinsic motivation and a reduction in amotivation. These results support the concept that VFB not only facilitates learning but also improves learners' engagement and motivation.
This motivational effect is critical in adolescent population, where self-determination and autonomy-supportive environments play an important role in sustaining participation and learning [37,42]. In our study, the lower amotivation score observed in the EG compared to the CG may be attributed to the effect of the AI intervention. For this perspective, the environment of CG training suffers from the absence of three needs: action effectiveness, autonomy and peer group affiliation, which contributes to the development of amotivation. Animated feedback, in the case of our study through avatars generated by DeepMotion 3D, can be seen as a form of playful learning, enhancing the perceived relevance and enjoyment associated with the task [52]. The absence of significant differences observed in extrinsic motivation suggests that the effects observed stem mainly from processes related to intrinsic motivation.

Practical Applications

The use of AI-based VFB appears to offer promising pedagogical benefits, particularly in PE and grassroots soccer training. By facilitating self-assessment, improving attentional focus, and fostering autonomy, this strategy supports a more learner-centred pedagogy aligned with current educational paradigms. Additionally, the improved biomechanical alignment could contribute to injury prevention strategies, particularly given the high-risk nature of tackling [35,38].
However, several limitations should be noted. First, the sample size was relatively small, limiting the generalizability of findings. Second, the duration of the intervention (six weeks) may not be sufficient to induce significant progress on the most complex movements like balance and sliding. And finally, while the AI system generated realistic animations, the fidelity of motion capture using standard video may be inferior to marker-based systems.

Conclusions

This study provides strong evidence that AI-assisted VFB using 3D animated motion capture significantly improves the acquisition of tackling techniques in youth soccer. The intervention not only improved technical execution and biomechanical alignment, but also increased intrinsic motivation, suggesting strong potential for AI-enhanced pedagogy in physical education and sports training contexts. These findings pave the way for innovative, evidence-based instructional practices that integrate motor learning optimization with increased learner engagement. Future research should explore the potential of multimodal feedback combinations, such as integrating video, tactile, and verbal cues, to further enhance training effectiveness. Additionally, studies are needed to assess long-term skill retention and transfer in competitive environments, as well as to examine the effects of these approaches on diverse populations, including women, different age groups, and different skill levels.

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Informed Consent Statement

The study's objectives and procedures were explained to the players, who then signed an informed consent form. All procedures complied with the Declaration of Helsinki (updated version of 2013, Fortaleza).

Ethical Committee approval

Protocol approved by the local research ethics committee (N: UR18JS01), National Observatory of Sport, Tunis, Tunisia.

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Topic

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Conflicts of interest

The authors have no conflicts of interest to declare.

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Author-s contribution

Conceptualization, M.S.B. and Y.R; methodology, M.S.B and H.M.; software, Y.R., S.V., G.A.; validation, J.P.; formal analysis, M.S.B.; investigation, Y.R.; resources, Y.R.; data curation, Y.R. and G.A.; writing—original draft preparation, S.H., S.V., J.P. and Y.R; writing—review and editing, Z.N. and G.R.; visualization, J.P.; All authors have read and agreed to the published version of the manuscript

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