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RESEARCH ARTICLE

Offline-Priority Embodied AI Feedback in Rural Physical Education: Effects on Task-Specific Body-Awareness Expression and Standing Long Jump Performance

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Abstract: In rural low-resource physical education settings, whether an offline-priority embodied AI feedback protocol is feasible and can improve students' task-specific expression of bodily sensations still requires empirical testing. This quasi-experimental study involved 72 first-year rural high school students (36 males and 36 females) randomly assigned to either the embodied AI group or the traditional AI feedback group. Both groups completed a 3-week standing long jump intervention (one 45–60 minute class per week, with 8 attempts per class). The experimental group used an offline-priority mobile learning ecosystem—teacher smartphone rapid key frame capture, data cable offline upload, local server AI processing, and iFlyTek voice input—to guide the "awareness–prediction–re-practice" loop, while the control group received only traditional technical feedback. The teacher circulated between the two groups during instruction. Linear mixed-effects models and Bootstrap mediation analysis were employed to examine the effects. Results showed that standing long jump distance improved by approximately 13% in both groups (embodied AI group: +13.13%; traditional AI group: +13.11%), with a non-significant time × group interaction ($p > 0.05$). However, the embodied AI group demonstrated significantly higher task-specific body-awareness expression scores than the control group (Cohen's $d = 3.239$, $p < 0.001$). Mediation analysis indicated that task-specific body-awareness expression did not significantly mediate the relationship between group assignment and improvement in jump performance. The findings suggest that an offline-priority embodied AI feedback protocol is feasible in rural low-resource environments and effectively enhances students' ability to describe, monitor, and predict bodily sensations in the specific context of standing long jump practice. However, it did not produce superior short-term gains in standing long jump performance compared with traditional AI feedback. Because the embodied protocol necessarily involved more dialogue turns and reflection time, future studies should employ yoked designs to isolate the independent effects of feedback type and interaction dosage.

Keywords: embodied AI feedback, task-specific body-awareness expression, rural low-resource physical education, standing long jump, offline-priority mobile learning ecosystem

1 Introduction

1.1 Research Background

Rural high school physical education faces practical challenges such as teacher shortages, limited facilities and equipment, and insufficient feedback, leaving students in a "practice blind spot." Feedback is a key instructional method for promoting motor skill learning in physical education (Han et al., 2022). Although AI technologies have shown promise in improving movement quality and motivation in physical education (Ma et al., 2025; He & Wei, 2025), most existing studies have been conducted in urban or laboratory settings with abundant resources. Empirical research on the adaptation of AI feedback in rural low-resource classrooms remains limited.

Embodied cognition theory posits that body awareness (proprioception) is central to motor skill learning (Faella et al., 2025; Musculus et al., 2021). Guiding students to externalize bodily sensations, monitor changes, and form predictions may facilitate motor learning. However, controlled studies examining embodied AI feedback in authentic rural physical education classrooms, with task-specific body-awareness expression as a key variable, are still scarce. This gap forms the starting point of the present study.

1.2 Research Questions and Significance

The primary research question is: In a rural low-resource setting, can an offline-priority embodied AI feedback protocol improve students' task-specific body-awareness expression during standing long jump practice? Secondary questions include: (1) Are there differences between the embodied AI and traditional AI groups in the dimensions of task-specific body-awareness expression? (2) Do the two groups differ in standing long jump performance and learning process indicators? (3) Does task-specific body-awareness expression mediate the relationship between group assignment and improvement in motor performance?

The theoretical significance lies in testing embodied AI feedback in authentic rural low-resource contexts. The practical significance is to explore a low-threshold, offline-priority implementation pathway suitable for rural high schools with single devices and circulating teacher guidance. At the policy level, this study provides only a preliminary classroom-level example from one rural school with a small sample and short intervention; multi-center, long-term research is needed before broader generalization.

1.3 Research Innovations

This study has three main innovations. First, it constructed an offline-priority mobile learning ecosystem (teacher smartphone capture + data cable offline upload + local server AI processing + voice input) that enables embodied feedback loops without one-to-one devices, embodying the principle of "technology adaptation rather than technology stacking."

Second, it employed a tightly controlled quasi-experimental design comparing two AI feedback protocols that differed only in embodied reflection and prediction prompts, with identical practice frequency, teacher procedures, and AI model versions. This design allows focused examination of task-specific body-awareness expression.

Third, it incorporated multi-source data and mechanism analysis using linear mixed-effects models and Bootstrap mediation, while transparently reporting interaction dosage as a potential confound.

1.4 Overview of Research Design

This study adopted a quasi-experimental design conducted in a natural rural high school classroom. Although students were stratified and randomly assigned at the individual level by gender, the study is described as quasi-experimental because it was implemented in a natural classroom context with limited control over contamination, teacher expectations, and classroom-level influences. Seventy-two first-year students (36 males, 36 females; mean age 15.8 years) were randomly assigned to the embodied AI group (n = 36) or the traditional AI group (n = 36). Baseline standing long jump distance was balanced between groups ($t = -0.244$, $p = 0.808$). The intervention lasted 3 weeks, with one 45–60 minute class per week and 8 attempts per class.

The independent variable was group (embodied AI feedback protocol *vs*. traditional AI feedback protocol). The mediating variable was task-specific body-awareness expression (0–9 point coding scale). The dependent variable was standing long jump distance (average of 8 attempts per week). Data were analyzed using linear mixed-effects models and Bootstrap mediation analysis.

1.5 Research Hypotheses

Based on embodied cognition theory and motor skill learning literature, the following hypotheses were proposed:

H1: Both groups will show significant improvement in standing long jump distance during the 3-week intervention (significant main effect of time).

This is based on general evidence that feedback promotes motor learning (Han et al., 2022).

H2: The embodied AI group will show significantly greater improvement in task-specific body-awareness expression than the traditional AI group.

This stems from the embodied AI protocol's systematic guidance of the "awareness–prediction–re-practice" loop.

H3: The embodied AI group will show significantly greater improvement in standing long jump distance than the traditional AI group (significant time × group interaction).

Given the rural low-resource context, short intervention duration, and cumulative nature of translating awareness into skill, this hypothesis is treated as exploratory.

H4: Task-specific body-awareness expression will mediate the relationship between group assignment and improvement in standing long jump distance.

2 Literature Review

2.1 AI Feedback and Motor Skill Learning

Feedback is a key instructional method for promoting motor skill learning in physical education. Han et al. (2022) found through trial sequential meta-analysis that feedback interventions have a significant positive effect on motor skill performance (SMD = 0.47). Recent studies have introduced AI into physical education feedback systems. Ma et al. (2025) demonstrated that an AI real-time feedback system based on posture recognition improved movement quality and self-directed learning in college students. He and Wei (2025) showed that augmented reality real-time feedback enhanced both motor skills and intrinsic motivation in youth team sports. However, most of these studies were conducted in urban or laboratory settings with high resources; adaptation to rural low-resource classrooms remains under-researched.

2.2 Embodied Cognition Theory and Body Awareness

Embodied cognition theory emphasizes that cognitive processes are deeply rooted in the dynamic interaction between the body and the environment (Varela et al., 1991; Clark, 2008). Musculus et al. (2021) highlighted the bidirectional predictive relationship between interoception and movement states in constructing the minimal self. Faella et al. (2025) concluded in their scoping review that body awareness and proprioception play a core role in motor skill acquisition in school physical education. Liang et al. (2025) found that embodied interventions more effectively reshape cognitive trajectories through body-environment interaction patterns compared with purely cognitive interventions. These theoretical foundations support embodied AI feedback, yet controlled empirical studies in authentic rural classrooms focusing on task-specific body-awareness expression remain scarce.

2.3 Embodied AI Feedback and Task-Specific Body-Awareness Expression

Embodied AI emphasizes forming an "awareness–prediction–re-practice" closed loop through visual and linguistic multimodal feedback. Existing AI feedback research has largely focused on technical correction rather than systematically guiding students to externalize bodily sensations, monitor changes, and make predictions (Ma et al., 2025; Tohănean et al., 2025). The construct of "task-specific body-awareness expression" in this study refers to students' ability to describe, monitor, and predict bodily sensations within a particular motor task (standing long jump). This is distinct from generalized "body awareness" or "proprioceptive improvement" and more closely reflects the verbal behavior and reflective processes trained by the intervention. Prior literature has not examined the effects of an offline-priority embodied AI protocol on this task-specific capacity in rural low-resource physical education.

2.4 Adaptation of AI Education in Rural Low-Resource Environments

Rural schools face structural challenges including the digital divide, weak infrastructure, and insufficient teacher training (Chen et al., 2025; López Costa, 2025). Tohănean et al. (2025) noted that while AI/ICT integration in physical education can provide personalized feedback, unstable networks and single-device environments in rural settings hinder direct transplantation of high-resource solutions. Studies on mobile learning and low-infrastructure solutions (Drolia et al., 2022; Samala et al., 2025; Uğraş et al., 2024) highlight their value in resource-constrained contexts. However, empirical cases of offline-priority, teacher-orchestrated embodied AI feedback in authentic high school physical education classrooms are extremely limited.

2.5 Summary of Literature and Research Gap

In summary, while AI feedback can support motor skill learning and embodied cognition theory underscores the importance of bodily reflection and self-monitoring, existing research rarely tests embodied AI feedback protocols on task-specific body-awareness expression in authentic rural physical education settings, nor does it separate awareness expression from short-term motor performance gains under strong controls. This study addresses these gaps through a quasi-experimental design in a rural high school using an offline-priority mobile learning ecosystem.

3 Research Methods

3.1 Participants and Design

This study employed a quasi-experimental design implemented in a natural rural high school classroom context. Although students were stratified and randomly assigned at the individual level by gender, the study is described as quasi-experimental because it was conducted in a natural classroom setting with limited control over contamination, teacher expectations, and classroom-level influences. Seventy-two first-year students (36 males, 36 females; mean age 15.8 years) were randomly assigned to the embodied AI group (n = 36) or the traditional AI group (n = 36). Baseline standing long jump distance was balanced (t = -0.244, p = 0.808). The intervention lasted 3 weeks, with one 45–60 minute class per week and 8 attempts per class. (see Table 1)

Table 1 Baseline Balance Table of Standing Long Jump Performance

Group	Sample Size (n)	Males (n)	Females (n)	Mean (cm)	SD	t value	p value
Control (Traditional AI)	36	18	18	172.91	28.49	-0.244	0.808
Experimental (Embodied AI)	36	18	18	174.36	21.66	–	–

3.2 Intervention Content and Control Arrangements

The experimental group used the embodied AI feedback protocol. After each jump, the teacher captured 3–5 seconds of key video with a smartphone, extracted key frames, and uploaded them via data cable to a local server. Students described bodily sensations using voice input. The AI combined the images and descriptions to analyze performance and guide students to predict bodily changes for the next attempt, forming an “awareness–prediction–re-practice” loop. The control group received traditional AI feedback that provided only technical improvement suggestions based on the images without requiring description of bodily sensations.

3.2.1 Clear Distinction of Feedback Mechanisms

Both groups used the same AI model (llava-phi3:mini, locally deployed) and processed identical visual materials. The only systematic difference lay in prompt design. The embodied AI group prompt required the AI to affirm the student’s sensation, point out related technical observations from the image, and guide specific predictions. The traditional AI group prompt requested only 1–2 direct technical suggestions.

3.2.2 Interaction Time and Reflection Time Note

Process data showed that the embodied AI group had more dialogue turns (5.8 *vs.* 3.1), longer body sensation descriptions, and more reflection time. This is an inherent feature of the embodied design but also constitutes a potential confound: the experimental group received not only “embodied-type” feedback but also more opportunities for dialogue and higher practice engagement. The study cannot fully separate the independent effects of feedback type and interaction dosage. Future research should employ strict yoked designs matching total interaction duration or dialogue turns.

3.3 Technical Support and Inclusive Design in Teaching Implementation

To accommodate unstable networks, limited equipment, and varying student digital literacy in rural high schools, this study built a low-threshold, offline-priority implementation framework. The teacher used an ordinary desktop computer as a local server running Open WebUI + Ollama (llava-phi3:mini). Students logged in using a local IP address and unified password. Key frame capture used a “teacher single smartphone rapid shooting + data cable upload” offline mode. Students used iFlyTek voice input to describe bodily sensations, greatly lowering operational barriers.

3.4 Data Collection and Analysis

Quantitative data included standing long jump distance and task-specific body-awareness expression scores (0–9 point coding scale). Process data included AI dialogue records and teacher logs. Qualitative data included student reflection cards.

3.4.1 Task-Specific Body-Awareness Expression Coding Scale (Core Measurement Tool)

Task-specific body-awareness expression was quantified using a researcher-developed 0–9 point coding scale. The scale contains three dimensions (0–3 points each): Specificity of Proprioceptive Description, Awareness of Change & Predictability, and Alignment with AI Feedback.

Important Note on Measurement Reactivity: The embodied AI group was explicitly trained to produce the verbal behaviors rewarded by the coding scale (specific descriptions, change monitoring, prediction, and alignment with AI feedback). Consequently, scores largely reflect task-specific expressive behavior learned within the intervention rather than generalized proprioceptive ability or broad embodied awareness. The very large effect size at Week 3 (d = 3.239) should be interpreted with caution. This study strictly limits interpretation to improvement in task-specific body-awareness expression within the standing long jump feedback activity. Future research should introduce measures independent of AI (e.g., unprompted think-aloud protocols or movement imagery questionnaires) to test transfer effects.

3.4.2 Statistical Analysis

Linear mixed-effects models were fitted in R (lme4::lmer) with Week 1 as the reference level for time and the embodied AI group as the reference category for group. The model formula was:

Model assumptions were met. Between-group comparisons of body-awareness expression scores used independent samples t-tests with Welch correction, reporting exact p-values ($p <$ 0.001), degrees of freedom, Cohen's d, and 95% CI, with Bonferroni correction for multiple comparisons (adjusted α = 0.0125). Mediation analysis used Bootstrap (5000 resamples). Because the indirect effect was non-significant and the 95% CI included zero, the study explicitly states that task-specific body-awareness expression did not significantly mediate the relationship between group assignment and improvement in standing long jump performance. The outcome variable for mediation was improvement from Week 1 to Week 3 (consistent with the time-effect analysis in the mixed model).

3.5 Ethics and Data Privacy

Ethics approval was obtained from the Ethics Review Committee of Cangxian Middle School and the Basic Education Division of Cangzhou Municipal Education Bureau (approval number available to the editor upon reasonable request, omitted here to protect minor participants). All procedures complied with the Declaration of Helsinki and relevant Chinese regulations.

Written informed consent was obtained from legal guardians of all participating students, and students provided oral assent. Consent forms explicitly stated that videos and photos would be used only for research analysis and would not be publicly disseminated. Guardians were clearly informed that students' use of iFlyTek voice input might involve temporary cloud-based ASR processing (standard commercial API behavior) but that no long-term audio recordings would be stored. This risk was assessed as low and necessary; it was disclosed in the consent forms. Any images potentially used for publication would be face-blurred and require additional guardian consent. All raw data were strictly anonymized. Only the research team had access to original data. Data will be retained for 3 years after study completion and then permanently deleted.

4 Results

4.1 Motor Skill Improvement

Both groups showed significant improvement in standing long jump distance over the 3-week intervention, but the magnitude of improvement was nearly identical (see Figures 1 and 2). The embodied AI group improved from 181.15 cm in Week 1 to 204.38 cm in Week 3

(+13.13%); the traditional AI group improved from 180.27 cm to 203.29 cm (+13.11%). Linear mixed-effects models revealed a significant main effect of time but a non-significant time × group interaction ($p > 0.05$), indicating that the embodied AI feedback protocol did not produce superior short-term gains in standing long jump distance compared with traditional AI feedback. (see Table 2)

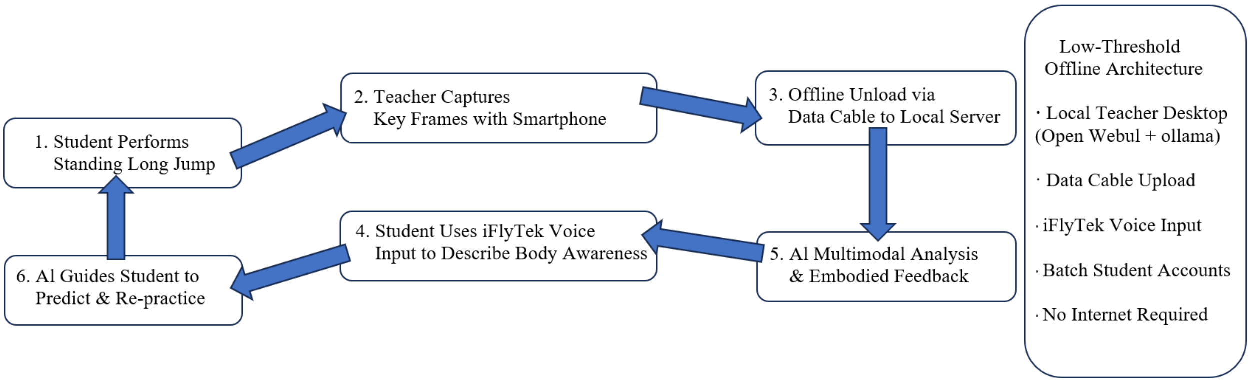

Figure 1 Embodied AI feedback closed-loop framework in rural low-resource environments

The diagram illustrates the complete offline-priority implementation process: teacher smartphone rapid key frame capture, data cable offline upload, local server AI processing, iFlyTek voice input, and the "awareness–prediction–re-practice" loop.

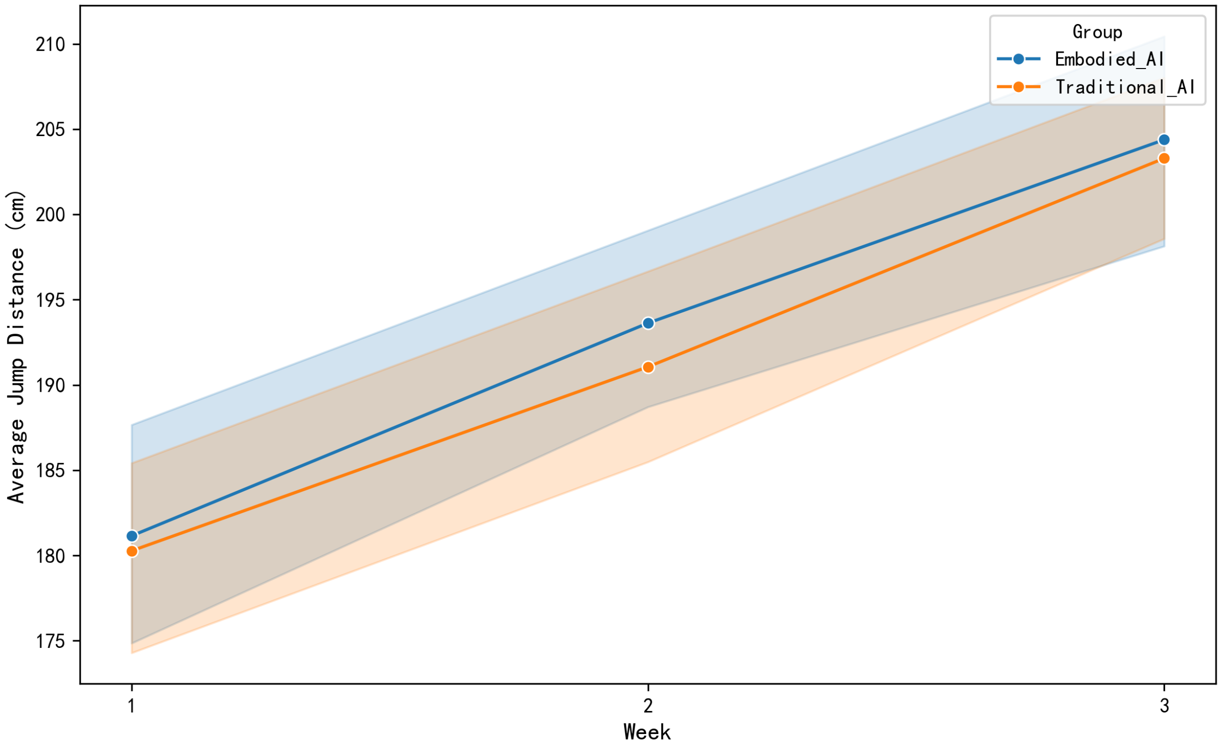

Figure 2 Three-week progress trajectories of standing long jump distance in both groups (mean ± 95% CI). time × group interaction, $p > 0.05$.

Table 2 Weekly Distance Improvement Quantitative Table

Group	Week	Average Distance (cm)	% Improvement
Embodied AI	1	181.15	–
Embodied AI	2	193.62	7.26
Embodied AI	3	204.38	13.13
Traditional AI	1	180.27	–
Traditional AI	2	191.06	6.15
Traditional AI	3	203.29	13.11

4.2 Development of Task-Specific Body-Awareness Expression

Task-specific body-awareness expression was quantified using the 0–9 point coding scale. The embodied AI group's weekly mean total score improved from 6.84 in Week 1 to 8.24 in Week 3; the traditional AI group improved from 4.46 to 5.40. The between-group difference at Week 3 was highly significant (t = 13.74, $p < 0.001$, Cohen's d = 3.239; see Figures 3 and 4).

It must be emphasized that this very large effect size should be interpreted cautiously. The embodied AI group was systematically trained to produce the specific verbal behaviors measured by the coding scale (detailed descriptions, change monitoring/prediction, and alignment with AI feedback). Therefore, the scores primarily reflect task-specific expressive behavior learned within the AI-assisted standing long jump feedback activity rather than generalized proprioceptive ability or broad embodied awareness.

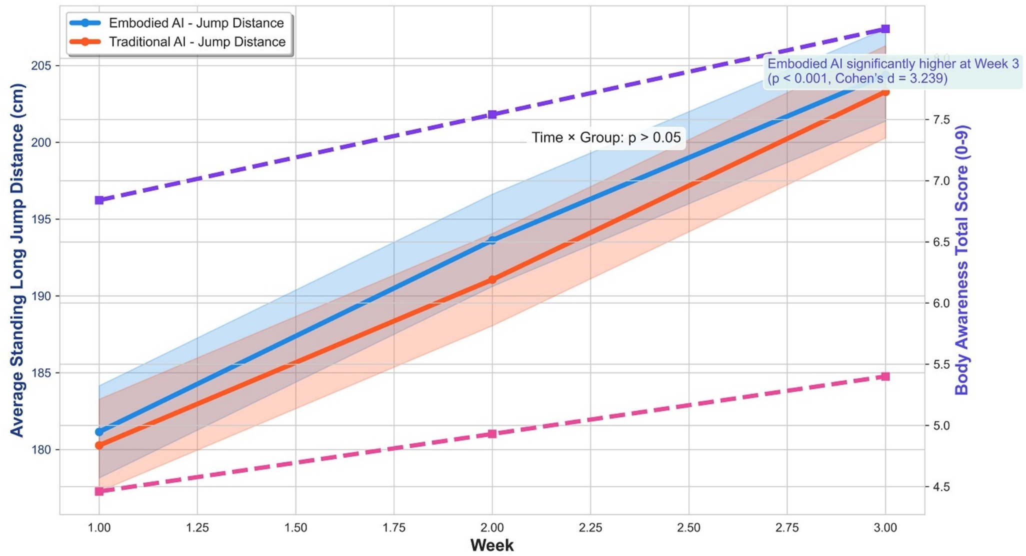

Figure 3 Three-week trajectories of standing long jump distance and task-specific body-awareness expression in both groups (dual Y-axis)

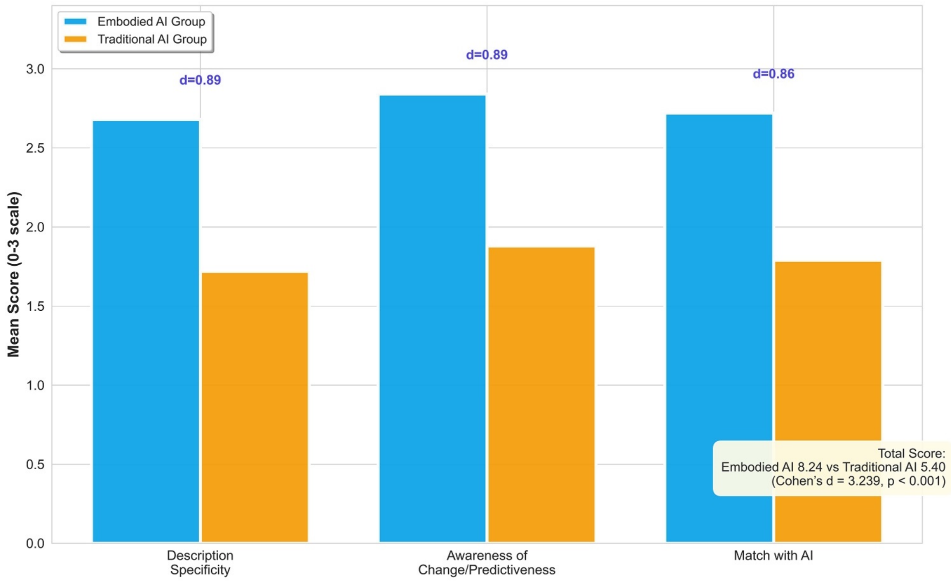

Figure 4 Between-group comparison of three sub-dimensions of task-specific body-awareness expression at Week 3

Blue and orange solid lines represent standing long jump distance for the two groups; the purple dashed line represents task-specific body-awareness expression scores for the embodied AI group. Time $\times$ group interaction, $p > 0.05$; embodied AI group significantly higher at Week 3, Cohen's d = 3.239. (see Table 3)

The embodied AI group scored significantly higher than the traditional AI group on Description Specificity, Awareness of Change/Predictiveness, and Alignment with AI Feedback.

Table 3 Week 3 Task-specific Body-awareness Expression Between-Group Differences

Indicator	Embodied AI Mean	Traditional AI Mean	Difference	t value	p value	Cohen's d
Description Specificity	2.68	1.72	0.95	11.108	< 0.001	2.618
Awareness of Change/Predictiveness	2.84	1.88	0.95	10.531	< 0.001	2.482
Alignment with AI Feedback	2.72	1.79	0.93	9.738	< 0.001	2.295
Total Score	8.24	5.40	2.84	13.74	< 0.001	3.239

4.3 Process Evidence and Qualitative Supplement

AI dialogue process data showed that the embodied AI group had significantly more dialogue turns, longer body sensation descriptions, and more embodied AI guidance instances than the control group (Cohen's d = 2.314–3.838, $p < 0.001$; see Table 4). Teacher log thematic analysis also indicated higher scores for the embodied AI group on themes of "body-awareness development," "autonomous practice and iteration," and "reflection depth and emotion."

These process differences partly stem from the design requirements of the embodied AI protocol (which necessitates more dialogue and reflection) and also constitute a potential confounding factor.

Table 4 Week 3 Key AI Dialogue Process Indicators – Between-Group Differences

Indicator	Embodied AI Mean	Traditional AI Mean	Difference	t value	p value	Cohen's d
Dialogue Turns	5.8	3.1	2.7	5.175	< 0.001	2.314
Body Sensation Description Word Count	54.7	27.6	27.1	8.502	< 0.001	3.802
Embodied AI Guidance Instances	3.5	0.5	3.0	8.581	< 0.001	3.838

4.4 Mediation Analysis

Bootstrap mediation analysis (5000 resamples) showed that the indirect effect of task-specific body-awareness expression between group assignment and improvement in standing long jump distance from Week 1 to Week 3 was 0.024, with 95% CI [-1.549, 1.660] containing zero; the mediation effect was non-significant. This study explicitly states that task-specific body-awareness expression did not significantly mediate the relationship between group assignment and improvement in standing long jump performance. (see Table 5)

Table 5 Key Fixed Effects of Linear Mixed Effects Model

Fixed Effect	Coefficient	SE	z value	p value	95% CI Lower	95% CI Upper
Intercept	181.150	2.965	61.089	< 0.001	175.338	186.962
C(Week)[T.2]	12.475	1.560	7.996	< 0.001	9.417	15.533
C(Week)[T.3]	23.229	1.560	14.889	< 0.001	20.171	26.287
C(Group)[T.Control]	-0.877	4.194	-0.209	0.8343	-9.096	7.342
C(Week)[T.2] $\times$ C(Group)[T.Control]	-1.689	2.206	-0.765	0.4441	-6.013	2.636
C(Week)[T.3] $\times$ C(Group)[T.Control]	-0.214	2.206	-0.097	0.9228	-4.538	4.111

Note: The embodied AI (experimental) group served as the reference category for the group factor. z-values approximate t-values in large samples. Model supplementary statistics: Random intercept variance τ^2 = 383.86, residual variance σ^2 = 208.61, ICC = 0.648 ($>$ 0.05). Marginal R^2 = 0.136, conditional R^2 = 0.696. All model assumptions were met.

5 Discussion

5.1 Main Findings

Through a quasi-experimental comparison of two AI feedback protocols, this study revealed a mixed but informative pattern. In a rural low-resource high school physical education setting, the embodied AI feedback protocol and the traditional AI feedback protocol produced similar effects on standing long jump distance improvement. The embodied AI group improved by 13.13% and the traditional AI group by 13.11% from Week 1 to Week 3, with a non-significant time $\times$ group interaction ($p > 0.05$). However, the embodied AI group showed significantly higher task-specific body-awareness expression scores than the control group (Cohen's d = 3.239, $p < 0.001$).

These results indicate that an offline-priority embodied AI feedback protocol is feasible in authentic rural classrooms and effectively enhances students' ability to describe, monitor, and predict bodily sensations within the specific context of standing long jump practice. Nevertheless, this improvement in task-specific expression did not translate into superior short-term gains in standing long jump performance compared with traditional AI feedback within the 3-week intervention.

The study cannot fully separate the independent effects of "feedback type" and "interaction dosage." The embodied AI group, due to protocol design requirements, produced more dialogue turns, longer reflection time, and greater language output. While this is an inherent mechanism promoting task-specific body-awareness expression, it also constitutes a potential confound. Future research should employ strict yoked designs to isolate these effects more precisely.

5.2 Theoretical Contributions

The unique value of this study lies in providing empirical evidence for embodied AI applications in low-resource rural educational contexts. By constructing an offline-priority mobile learning ecosystem (teacher smartphone capture + data cable offline upload + local server AI processing + voice input), the study successfully implemented an embodied feedback loop in a real rural high school classroom with single devices and circulating teacher guidance.

Within the embodied cognition framework, the study found a short-term dissociation between improvement in task-specific body-awareness expression and improvement in motor performance. This aligns with classic theories of explicit–implicit learning and declarative–procedural knowledge transformation (Fitts & Posner, 1967; Anderson, 1982). The embodied AI protocol first activated explicit reflection and declarative knowledge levels (reflected in significantly improved task-specific expression scores), whereas improvement in standing long jump distance relies more on the automation and implicit optimization of procedural motor programs, which typically requires longer periods of repeated practice. Thus, the 3-week intervention was sufficient to change students' reflective expression but insufficient for this change to be fully internalized into measurable additional motor performance gains.

This finding offers a new time-dynamic perspective for mechanism research on embodied AI in physical education: improvement in task-specific body-awareness expression may serve as a preceding or parallel process to motor skill learning rather than a direct sufficient condition for performance improvement in the short term. The study also underscores the design principle of "technology adaptation rather than technology stacking" in resource-constrained environments, providing a replicable practical example for low-resource educational technology implementation research.

5.3 Potential Practical and Policy Implications (Cautious Version)

The low-threshold, offline-priority embodied AI framework constructed in this study provides a preliminary classroom-level empirical case for applying AI feedback in rural high school physical education. The framework effectively reduces requirements for digital literacy and equipment, enabling embodied feedback without stable internet or one-to-one devices, making it suitable for the actual conditions of rural schools.

At the practical level, this design can serve as a reference for other motor skill teaching scenarios and similar low-resource contexts. Future development of standardized, modular offline embodied AI prompt libraries and simple teacher training materials could further lower implementation barriers.

At the policy level, because this study was conducted in only one rural high school with 72 students and a 3-week intervention, the results should be viewed as a preliminary micro-level example. Local education authorities may refer to this low-cost, operable implementation pathway when formulating "AI + Physical Education" plans, but multi-center, long-term research is needed to verify generalizability and sustainability.

5.4 Limitations and Future Research Directions

This study has the following limitations:

(1) The short intervention period (only 3 weeks) may have been insufficient for improvements

in task-specific body-awareness expression to translate into measurable additional gains in motor performance. Future research should extend the intervention to 8–12 weeks and include delayed retention tests and transfer tasks.

(2) The sample came from only one rural high school (n = 72), limiting external validity. Multi-center, multi-regional replication studies are needed.

(3) The body-awareness coding scale is highly aligned with the embodied AI intervention task. Students in the experimental group were explicitly trained to produce the verbal behaviors measured by the scale, which may have artificially inflated between-group differences (d = 3.239). Future research should introduce measures independent of AI (e.g., unprompted think-aloud protocols or movement imagery questionnaires).

(4) Interaction dosage constitutes a potential confounding factor. Future studies should employ strict yoked designs.

(5) The study lacked objective biomechanical indicators. Future research could incorporate simple wearable devices or video motion analysis.

(6) No retention tests or transfer tasks were conducted. Future research must include retention assessments (2–4 weeks post-intervention) and tests of transfer to other movements or contexts.

(7) Potential covariates and moderators (e.g., gender, motivation, prior sports experience, digital literacy) were not included. Future research should measure these variables and conduct extended analyses.

(8) The study was implemented in a natural classroom context with possible limited contamination and teacher expectancy effects. Results should be interpreted with appropriate caution.

Future research directions include: conducting 8–12 week multi-center quasi-experimental or cluster-randomized controlled studies; developing standardized offline embodied AI prompt libraries across sports; combining biomechanical and self-report multimodal assessment; and conducting differentiated design research for student subgroups with varying digital literacy and language expression abilities.

These limitations do not negate the contributions of this study but clearly define its applicable boundaries and space for subsequent optimization.

Ethics Approval

This study received ethics approval from the Ethics Review Committee of Cangxian Middle School and the Basic Education Division of Cangzhou Municipal Education Bureau. The approval number is omitted in the main text to protect minor participants but is available to the journal editor upon reasonable request with appropriate confidentiality measures. All procedures complied with the Declaration of Helsinki (2013 revision) and relevant Chinese regulations.

Informed Consent and Minor Protection

Written informed consent was obtained from the legal guardians of all participating students (mean age 15.8 years), and students provided oral assent. Consent forms detailed the research purpose, procedures (including video/photo capture, voice description, AI feedback, and reflection cards), potential risks, benefits, data use, right to withdraw, and absence of academic penalty. All materials used language easily understood by students and explicitly stated that videos and photos would be used only for research analysis and would not be publicly disseminated.

Data Storage, Privacy Protection, and Special Considerations for Minors

Local-priority storage: Except for temporary cloud-based ASR processing possibly involved in iFlyTek voice input, all key frame photos, AI dialogue records, reflection cards, and teacher logs were stored on the teacher's local password-protected server. Data will be retained for 3 years after study completion and then permanently deleted.

iFlyTek voice input note: When students used iFlyTek voice input to describe proprioceptive sensations, voice data may have undergone temporary processing through iFlyTek's cloud-based ASR service (standard commercial API behavior). No long-term audio recordings were stored.

The research team assessed this risk as low and necessary; guardians were explicitly informed of this processing method, its temporary nature, and the absence of long-term audio storage in the informed consent forms.

Identifiable image processing: Any images potentially used for publication will undergo facial blurring and require additional written guardian consent.

Access permissions and classroom privacy: Only the research team had access to original data. Photos were processed only on the teacher's local computer and were not displayed on classroom screens.

Data anonymization: All data used for analysis and sharing had direct and indirect identifying information removed.

Data Availability

To protect participant privacy (especially minors), all raw data underwent strict anonymization. Anonymized process data can be provided to the corresponding author upon reasonable academic request under a signed confidentiality agreement and strict adherence to ethical standards. Summary statistics, intervention procedures, embodied prompts (version 10.0), and coding rules are included in the main text and supplementary materials for direct reuse.

Funding

This study received no external funding and was self-funded by the researcher.

AI Use Declaration

This study involves two types of AI systems:

(1) AI system used in research intervention: Open WebUI + Ollama (llava-phi3:mini model) deployed locally on the teacher's computer (fully local operation, no cloud upload); iFlyTek voice input method (may involve temporary cloud ASR processing, detailed in the Data Storage section).

(2) AI system used in manuscript preparation: Grok AI (xAI) was used only for language polishing, format assistance, reference formatting checks, and minor editing suggestions. All research design, data collection, statistical analysis, result interpretation, theoretical discussion, conclusion writing, and final revisions were independently completed by the author and are the author's responsibility. Grok did not participate in any substantive research content generation or data analysis.

The research team has reported the above AI use situation to the ethics review committee and school administration.

Conflicts of Interest

The author declares no conflicts of interest.

References

Anderson, J. R. (1982). Acquisition of cognitive skill. Psychological Review, 89(4), 369–406. https://doi.org/10.1037/0033-295x.89.4.369

Chen, R., Wu, Y., Chen, Z., & Zhou, P. (2025). Advancing educational equity in rural China: the impact of AI devices on teaching quality and learning outcomes for sustainable development. Frontiers in Psychology, 16. https://doi.org/10.3389/fpsyg.2025.1588047

Clark, A. (2008). Supersizing the Mind. https://doi.org/10.1093/acprof:oso/9780195333213.001.0001

Drolia, M., Papadakis, S., Sifaki, E., & Kalogiannakis, M. (2022). Mobile Learning Applications for Refugees: A Systematic Literature Review. Education Sciences, 12(2), 96. https://doi.org/10.3390/educsci12020096

Faella, P., Digennaro, S., & Iannaccone, A. (2025). Educational practices in motion: a scoping review of embodied learning approaches in school. Frontiers in Education, 10. https://doi.org/10.3389/feduc.2025.1568744

Fitts, P. M., & Posner, M. I. (1967). Human performance. Brooks/Cole.

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. https://doi.org/10.3390/ijerph192215361

He, X., & Wei, L. (2025). Real-time feedback enhances motor learning and motivation in youth team sports through augmented reality tools. Frontiers in Psychology, 16. https://doi.org/10.3389/fpsyg.2025.1661936

Liang, C., Zhi, J., Su, C., Xue, W., Liu, Z., & Ye, H. (2025). A Study on the Effects of Embodied and Cognitive Interventions on Adolescents' Flow Experience and Cognitive Patterns. Behavioral Sciences, 15(6), 768. https://doi.org/10.3390/bs15060768

López Costa, M. (2025). Artificial Intelligence and Data Literacy in Rural Schools' Teaching Practices: Knowledge, Use, and Challenges. Education Sciences, 15(3), 352. https://doi.org/10.3390/educsci15030352

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(1). https://doi.org/10.1186/s40561-025-00411-3

Musculus, L., Tünte, M. R., Raab, M., & Kayhan, E. (2021). An Embodied Cognition Perspective on the Role of Interoception in the Development of the Minimal Self. Frontiers in Psychology, 12. https://doi.org/10.3389/fpsyg.2021.716950

Samala, A. D., Papadakis, S., & Rawas, S. (2025). Global Insights into Mobile Learning in Higher Education: A PRISMA-Guided Bibliometric Analysis from 2007 to 2023. International Journal of Educational Reform. https://doi.org/10.1177/10567879251341869

Tohănean, D. I., Vulpe, A. M., Mijaica, R., & Alexe, D. I. (2025). Embedding Digital Technologies (AI and ICT) into Physical Education: A Systematic Review of Innovations, Pedagogical Impact, and Challenges. Applied Sciences, 15(17), 9826. https://doi.org/10.3390/app15179826

Uğraş, H., Uğraş, M., Papadakis, S., & Kalogiannakis, M. (2024). ChatGPT-Supported Education in Primary Schools: The Potential of ChatGPT for Sustainable Practices. Sustainability, 16(22), 9855. https://doi.org/10.3390/su16229855

Varela, F. J., Rosch, E., & Thompson, E. (1991). The embodied mind: Cognitive science and human experience. MIT Press. https://doi.org/10.7551/mitpress/6730.001.0001