Mobile tracking ecosystem on motor engagement and physical performance: a cluster-randomized trial

Ecosistema de seguimiento móvil sobre compromiso motor y rendimiento físico: ensayo aleatorizado por conglomerados

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Abstract

Introduction: Adolescent physical inactivity remains a significant public health challenge. In North African urban contexts, limited extracurricular infrastructure and sedentary behaviors contribute to physical deconditioning among secondary students.
Objective: This study examined the effects of a multi-component mobile tracking ecosystem on motor engagement and physical performance among Moroccan secondary students from contrasting socioeconomic backgrounds.
Methodology: A cluster-randomized controlled trial enrolled 295 urban adolescents (59% female; M age = 16.99 ± 0.82 years) across nine intact classes (experimental: n = 161; control: n = 134) for 12 weeks. The intervention combined personalized training protocols, free tracking applications (Strava, Google Fit), WhatsApp peer-support networks, and 12 autonomous community sessions. Motor engagement was assessed via systematic ALT-PE observation (κ ≥ .78); physical performance via Luc Léger shuttle run, Ruffier-Dickson index, and Killy wall-sit test.
Results: Motor Appropriate engagement increased by +21.9 percentage points in the experimental group (48.7% - 70.5%; d_z = 6.54, p < .001), while declining in controls. Physical fitness improved significantly: Luc Léger +1.54 paliers (+25.7%), Killy +26.3 s (+21.7%), Ruffier-Dickson −1.05 points (−27.4%; all p < .001). No significant engagement-fitness correlations were found (r = −.08 to .10, all p > .26).
Discussion: Intervention effects exceeded typical benchmarks for technology-enhanced physical education. Absence of socioeconomic moderation confirmed the equity potential of peer-pairing pedagogy in resource-constrained contexts.
Conclusions: A low-cost mobile tracking ecosystem substantially improves motor engagement and physical fitness in secondary school physical education, with effects equitably distributed across socioeconomic strata.

Keywords

Adolescent physical activity; cluster-randomized controlled trial; mobile tracking; motor engagement; physical education.

Resumen

Introducción: La inactividad física adolescente constituye un reto de salud pública, especialmente en contextos norteafricanos con infraestructura extraescolar limitada.
Objetivo: Este estudio examinó los efectos de un ecosistema multicomponente de seguimiento móvil sobre el compromiso motor y el rendimiento físico en estudiantes marroquíes de secundaria.
Metodología: Ensayo controlado aleatorizado por conglomerados (N = 295; 59% mujeres; M edad = 16.99 ± 0.82 años; 5 clases experimentales n = 161; 4 clases control n = 134; 12 semanas). La intervención combinó aplicaciones gratuitas (Strava, Google Fit), redes de apoyo entre pares (WhatsApp) y sesiones autónomas comunitarias. El compromiso motor se evaluó mediante ALT-PE (κ ≥ .78); el rendimiento físico mediante los tests de Luc Léger, Ruffier-Dickson y Killy.
Resultados: El compromiso motor apropiado aumentó +21.9 puntos porcentuales en el grupo experimental (48.7% - 70.5%; d_z = 6.54, p < .001). El rendimiento físico mejoró: Luc Léger +1.54 paliers (+25.7%), Killy +26.3 s (+21.7%), Ruffier-Dickson −1.05 puntos (−27.4%). No se encontraron correlaciones significativas entre compromiso y condición física (todas p > .26).
Discusión: Los efectos superaron los parámetros habituales. La ausencia de moderación socioeconómica confirmó el potencial equitativo de la pedagogía de emparejamiento entre pares.
Conclusiones: Un ecosistema de seguimiento móvil de bajo coste mejora el compromiso motor y la condición física de forma equitativa entre estratos socioeconómicos.

Palabras clave

Actividad física adolescente; aplicaciones móviles; compromiso motor; educación física; ensayo controlado aleatorizado.

Introduction

Adolescent physical inactivity constitutes a significant global health challenge requiring targeted pedagogical innovations. Over 80% of young people fail to meet recommended daily physical activity levels, contributing to rising obesity rates and declining cardiovascular fitness worldwide (Bull et al., 2020; World Health Organization, 2020). The COVID-19 pandemic accelerated these trends through extended school closures that decreased physical activity by 20% globally (Schmidt et al., 2020). Within North African educational contexts, these global trends are particularly evident: urban Moroccan secondary students demonstrate concerning patterns of physical deconditioning (Ben Rakaa et al., 2024b). Limited extracurricular infrastructure and pervasive screen-based sedentary behaviors exacerbate disengagement from structured physical activity (Dahlgren et al., 2021). Physical and psychosocial health conditions among students introduce additional barriers to inclusive participation that demand differentiated pedagogical responses (Ben Rakaa et al., 2024a, 2025). Traditional teacher-directed instructional models demonstrate systematic inadequacies in sustaining adolescent motivation during repetitive endurance training (Mateo-Orcajada et al., 2023b). These conventional approaches yield minimal fitness adaptations and substantial behavioral disengagement (Breed et al., 2024). This confluence of epidemiological urgency and pedagogical insufficiency necessitates innovative approaches integrating technological affordances with evidence-based instructional frameworks (Martín-Rodríguez & Madrigal-Cerezo, 2025). Emerging AI-enabled monitoring technologies further extend the scope of real-time physiological tracking in physical activity contexts (Sultan et al., 2024).

Mobile tracking technologies represent a promising pedagogical innovation grounded in self-determination theory's fundamental psychological needs of autonomy, competence, and relatedness. Recent empirical evidence demonstrates that these applications substantially enhance intrinsic motivation through personalized goal-setting mechanisms and immediate performance validation (Ibragimova et al., 2025). Wearable activity monitoring interventions have documented improvements in both physical activity volume and psychological mediators of sustained behavior change (Guijarro-Romero et al., 2023). Cluster-randomized trials conducted within North African educational systems reveal that multi-platform tracking ecosystems yield substantial improvements in motivational outcomes, with increases of 28.1% in intrinsic motivation alongside cardiovascular fitness markers demonstrating 40.3% improvements when systematically integrated within structured endurance training protocols (Moudettir et al., 2025b, 2025c). Multi-component technological ecosystems demonstrate superior effectiveness compared to single-application approaches by optimizing personalized learning pathways and sustaining engagement across diverse student populations (Hrušová et al., 2024). However, implementation science reveals persistent challenges including premature application abandonment attributable to interface complexity and usability concerns (Mateo-Orcajada et al., 2024b). Gender and academic year differences moderate intervention effectiveness, necessitating differentiated implementation strategies (Mateo-Orcajada et al., 2023a). Quality heterogeneity across commercially available adolescent fitness applications introduces additional implementation considerations (Mateo-Orcajada et al., 2024a). Nevertheless, systematic integration with evidence-based pedagogical frameworks substantially enhances implementation fidelity and behavioral outcomes (Gil-Espinosa et al., 2020; Moudettir et al., 2025a).

Academic Learning Time in Physical Education provides the conceptual and methodological foundation for rigorously examining technology-mediated pedagogical effectiveness through systematic behavioral observation rather than relying exclusively on self-reported outcomes (Siedentop, 1982). This validated framework enables precise quantification of educationally productive engagement by differentiating appropriate motor involvement from various off-task behavioral categories. Traditional classes typically achieve 40–60% appropriate motor engagement, with technological interventions potentially increasing this by 5–15 percentage points (Fu et al., 2017). Contemporary research establishes positive correlations between tracking application usage and increased effective motor learning time (Munn et al., 2024). Digital interventions can produce clinically meaningful improvements in adolescent cardiorespiratory capacity, with average gains of 8–12% over 8–12 week periods (Leone et al., 2024). Self-determination theory provides complementary theoretical scaffolding, positing that tracking applications incorporating autonomy-supportive features and competence-validating feedback mechanisms generate superior adherence trajectories by satisfying fundamental psychological needs (Ibragimova et al., 2025). Real-time performance feedback represents a particularly potent pedagogical mechanism, enabling students to calibrate exercise intensity appropriately and develop metacognitive awareness regarding their physiological responses during structured training sessions (Gil-Espinosa et al., 2022; Omarov et al., 2024; Oshanova et al., 2025). This convergence of behavioral observation methodologies, motivational psychology frameworks, and digital feedback technologies creates new opportunities for advancing physical education pedagogy beyond traditional instructional limitations.

Despite accumulating evidence supporting mobile tracking integration, significant gaps constrain both theoretical understanding and practical implementation guidance. Research systematically examining multi-component technological ecosystems on concurrent behavioral and physiological outcomes remains limited (Mateo-Orcajada et al., 2024a). The field requires more rigorous investigations employing validated observation frameworks rather than relying predominantly on self-reported measures, a methodological limitation that constrains both effect estimation and behavioral mechanism identification (Hrušová et al., 2024). The specific mechanisms through which real-time digital feedback influences sustained participation in structured endurance training protocols require further investigation to inform pedagogical design principles (Gil-Espinosa et al., 2022). Furthermore, the literature demonstrates systematic underrepresentation of diverse socioeconomic contexts, particularly within lower-middle-income educational systems where resource constraints and digital equity concerns introduce unique implementation challenges (Ben Rakaa et al., 2024b). Methodologically, the predominance of short intervention durations limits conclusions regarding sustainability of observed effects.

The present investigation addresses these significant gaps through a cluster-randomized controlled trial examining whether a multi-component mobile tracking ecosystem enhances motor engagement and physical performance among Moroccan secondary students during endurance training. Employing systematic ALT-PE behavioral observation alongside standardized fitness assessments, this study tests three theoretically grounded hypotheses. First, we hypothesize that the integrated tracking ecosystem will generate significantly greater improvements in appropriate motor engagement and significantly greater reductions in off-task behaviors relative to traditional instruction, by satisfying self-determination theory's fundamental psychological needs through personalized goal-setting and competence-validating feedback. Second, we hypothesize that experimental group participants will exhibit superior improvements in aerobic capacity, muscular endurance, and cardiovascular recovery compared to control group peers, reflecting exercise physiology principles linking enhanced behavioral engagement to greater training volume and superior physiological adaptations. Third, we hypothesize that positive correlations will emerge between motor engagement behaviors and physical performance outcomes, providing empirical evidence for the theorized mediating role of behavioral engagement in linking technological interventions to physiological improvements. Beyond testing these specific hypotheses, this investigation contributes to the literature on three distinct fronts. Methodologically, it employs systematic ALT-PE direct observation rather than self-reported measures, enabling precise behavioral quantification that most technology-enhanced PE studies lack. Theoretically, it examines a multi-component ecosystem integrating five concurrent elements rather than a single application, providing a more ecologically valid test of technology integration effectiveness. Contextually, it addresses the systematic underrepresentation of lower-middle-income North African educational systems in the evidence base, where digital equity constraints and resource limitations introduce unique implementation dynamics that findings from high-income contexts cannot adequately address (Gomes et al., 2024).

Method

This trial was retrospectively registered on the Open Science Framework following study completion (OSF: https://doi.org/10.17605/OSF.IO/XQ8NG) due to institutional constraints at study initiation. The study adhered to CONSORT-Cluster 2012 guidelines, received institutional ethical approval in accordance with international standards for educational research involving adolescents, and obtained written informed consent from all participants and legal guardians.

Participants

A total of 295 adolescent students (59.0% female; M age = 16.99 ± 0.82 years) from two strategically selected urban secondary schools in Casablanca, Morocco, representing contrasting socio-economic realities, one well-resourced and one resource-limited school, participated in this trial. This deliberate heterogeneity enabled examination of digital equity mechanisms in technology ecosystem implementation across diverse educational contexts characteristic of developing regions (UNESCO, 2021; Warschauer, 2003).

A priori power analysis using G*Power 3.1.9.7 for repeated measures ANOVA targeting d = 0.35 with α = .05 and power = .80, adjusted for clustering effects (ICC = 0.025) and 15% attrition, indicated n = 280 minimum. The achieved sample provided post-hoc power exceeding .90 for medium effect detection across primary outcomes. Nine intact classes (5 experimental, n = 161; 4 control, n = 134) with 24-30 students per class were enrolled to preserve ecological authenticity of natural classroom dynamics. Eligibility required age 15-19 years, regular PE participation, medical clearance, smartphone access through personal or family devices, and dual informed consent following ethical standards.

Computer-generated permuted block allocation with variable block sizes (2, 4, 6) stratified by school socio-economic profile was conducted by an independent statistician using R 4.3.0, with sealed opaque envelopes maintaining allocation concealment until enrollment completion. Randomization successfully balanced groups across all variables: demographics (age d = -0.037, p = .751; gender χ^2 = 0.52, p = .470), aerobic capacity (Luc Léger d = -0.004, p = .996; VO_2max d = -0.030, p = .811), cardiovascular recovery (Ruffier-Dickson d = -0.133, p = .283), and muscular endurance (Killy d = 0.036, p = .783), confirming comparability and justifying standard analytic approaches without baseline adjustment.

Procedure

This study implemented a theoretically-grounded four-component ecosystem designed to transform behavioral engagement through Self-Determination Theory supports (Deci & Ryan, 2000) while addressing socioecological barriers in resource-constrained contexts. The ecosystem comprised: (1) Excel-generated personalized endurance protocols calibrated to baseline capacity; (2) student-selected free applications (Strava, Google Fit, Samsung Health) enabling choice while accommodating device heterogeneity; (3) WhatsApp groups facilitating social support and collaborative problem-solving; (4) twelve self-directed community sessions promoting autonomous transfer with optional family participation.

To prevent digital inequalities, UDL-based peer-pairing (Rose & Meyer, 2002) guided dyad formation according to technological proficiency and device availability. Students lacking personal devices utilized family smartphones, transforming parents into active participants. Eight educators completed 8-hour training covering facilitation and technological troubleshooting.

The 12-week program comprised 36 sessions: 24 mandatory bi-weekly PE lessons plus 12 optional community sessions. The 12-week duration was selected on theoretical and empirical grounds: exercise physiology research indicates that a minimum of 8-12 weeks is required for measurable cardiorespiratory adaptations in adolescents (Mateo-Orcajada et al., 2024b; Leone et al., 2024), while behavior change literature suggests 10-12 weeks are necessary for mobile technology interventions to generate durable motivational shifts beyond initial novelty effects (Ibragimova et al., 2025). During the 12 optional community sessions, teachers adopted a consultative rather than directive role: they were available for technical troubleshooting and goal-setting guidance via the WhatsApp group channels but did not supervise sessions directly, thereby preserving the autonomous and self-directed character of out-of-school activity that is central to the SDT-based rationale of the intervention. Each maintained standardized structure: 10-minute preparation, 35-minute progressive running following periodized intensity (weeks 1-4: 60-75% maximal aerobic speed; weeks 5-8: 75-90%; weeks 9-12: 90-110%), and 10-minute recovery. Experimental participants autonomously managed sessions via applications; controls performed identical protocols through traditional teacher-directed delivery.

Implementation fidelity was verified through direct observation (25% sessions), objective technology metrics, teacher logs, and bi-weekly coordination meetings. Outcome assessors remained blinded when feasible.

Instrument

Academic Learning Time in Physical Education

This study employed systematic direct observation using the Academic Learning Time in Physical Education framework (Siedentop, 1982), culturally validated through Moroccan pilot testing with 50 students and expert consensus. ALT-PE quantifies time allocation across seven mutually exclusive behavioral categories constrained to sum to 100%: Motor Appropriate (on-task physical activity at appropriate difficulty), Motor Inappropriate (off-task motor behavior), Cognitive Engagement (instruction reception and strategic planning), Social Engagement (lesson-related peer interaction), Passive Waiting (idle transitional time), Out-of-Context Tasks (non-lesson activities), and Deviant Behavior (disruptive conduct).

Trained observers (n = 4; 12-hour standardized training) including the regional PE inspector who collaborated in the research process conducted continuous systematic observation throughout all 24 PE sessions, sampling approximately 33% of class participants per session via 6-second observe/6-second record interval coding during 35-minute main activity phases. Inter-observer reliability verification through double-coding of 20% of videos yielded strong agreement: Cohen's $\kappa = .87$ for Motor Appropriate, .83 for Motor Inappropriate, .81 for Passive Waiting, and .78-.85 for remaining categories. Following compositional data analysis recommendations (Fu et al., 2017), behavioral changes are reported as absolute percentage point differences, with 5 percentage points established as pedagogically meaningful threshold (approximately 2.75 minutes per session).

Aerobic Capacity

Cardiorespiratory fitness was assessed via the 20-meter progressive shuttle run test (Léger et al., 1988), a maximal graded exercise protocol requiring participants to run continuously between parallel lines while maintaining synchronization with progressively accelerating audio signals. The test terminated when participants could no longer maintain required pace for two consecutive shuttles or upon volitional exhaustion. Maximum stage (palier) served as primary indicator, with estimated VO_2max calculated using the validated age-specific equation: $VO_2max = 31.025 + 3.238X - 3.248A + 0.1536AX$, where X represents maximal running speed (km/h) and A denotes age (years). This assessment demonstrates strong concurrent validity ($r = .84$) with laboratory criterion measures and excellent test-retest reliability ($r = .89$).

Cardiovascular Recovery

The Ruffier-Dickson Index quantified cardiovascular adaptation to standardized exercise stress. Following five minutes rest, baseline heart rate (P_0) was measured using validated Polar H10 telemetry monitors ($r = .99$ versus ECG). Participants performed 30 deep knee bends in 45 seconds at controlled cadence, followed by immediate post-exercise (P_1) and one-minute recovery (P_2) measurements. Index calculated as $[(P_0 + P_1 + P_2) - 200] / 10$, with lower values indicating superior fitness. Established classification thresholds: excellent (<3), good (3-8), average (8-15), poor (15-20), or very poor (>20).

Muscular Endurance

Static lower-body muscular endurance was evaluated via the Killy isometric wall-sit test. Participants maintained seated position against wall with 90-degree hip/knee flexion (goniometer-verified), thighs parallel to floor, feet shoulder-width apart, and arms crossed over chest. Maximum duration was recorded until volitional exhaustion or form breakdown (hip or knee angle deviation exceeding 5 degrees). This assessment demonstrates good test-retest reliability (ICC = .93).

All assessments occurred at T0 and T1 following standardized protocols after 10-minute warm-up. Prior to baseline assessment, participants completed a single familiarization session for each physical test (Luc Léger, Ruffier-Dickson, Killy) to minimize learning effects and ensure standardized execution. Blinded assessors administered tests during morning hours (08:00-11:00).

Data analysis

All analyses employed SPSS 29.0 and R 4.3.0 following theoretically grounded protocols consistent with CONSORT-Cluster guidelines. Data screening included outlier detection (±3SD criteria) and assumption verification via Shapiro-Wilk normality tests, Levene's homogeneity of variance tests, and Mauchly's sphericity tests. Primary intention-to-treat analyses utilized repeated measures ANOVA with fixed effects for time, group, and Group × Time interaction, incorporating adjustments for nested structure. Intracluster correlations were modest (class: .015-.035; school: .000-.020), with clustering accounting for 1.5-4.5% of outcome variance, slightly higher for behavioral engagement variables (3.0-4.5%) & physical performance measures (1.5-4.0%).

Missing data evaluation (Little's MCAR: $\chi^2 = 18.47$, df = 21, p = .621) confirmed random patterns. Maximum likelihood estimation was applied, with complete data for all 295 participants (2.7% missing individual data points). Significant interactions were decomposed via simple effects with Bonferroni adjustment ($\alpha = .025$). Greenhouse-Geisser corrections applied when sphericity was violated.

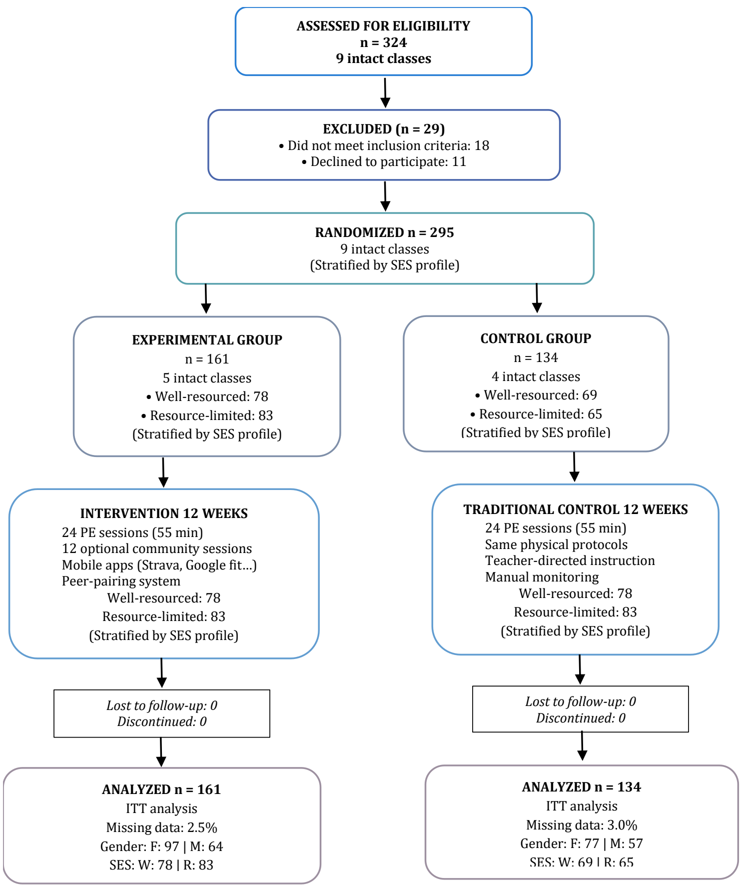
Effect sizes were quantified as partial η^2p (.01 small, .06 medium, .14 large) and Cohen's d with 95% CIs. For ALT-PE compositional data, recognizing that seven behavioral categories are constrained to sum to 100%, changes were reported as absolute percentage point differences, with 5 percentage points established as pedagogically meaningful threshold representing approximately 2.75 minutes of behavioral redistribution per session. Sensitivity analyses included complete-case analysis and per-protocol analysis (≥80% attendance). Exploratory Pearson correlations examined engagement-performance associations. Moderation analyses tested intervention variance by gender, socioeconomic status, baseline fitness tertile, and technology access using three-way mixed ANOVAs with Bonferroni correction (α = .0015 for 33 tests; α = .0045 for omnibus decomposition).

Results

Descriptive Statistics and Group Comparisons

Of 324 adolescents assessed, 295 met inclusion criteria (91.0% enrollment rate). Stratified randomization allocated 161 participants to experimental (60.2% female; M age = 16.97 ± 0.80) and 134 to control conditions (57.5% female; M age = 17.01 ± 0.84) across intact classes. The trial achieved 100% participant retention with 2.7% missing individual data points confirmed as completely random (Little's MCAR: $\chi^2 = 18.47$, df = 21, p = .621). Baseline equivalence was confirmed across demographics (age: $t_{293} = 0.43$, p = .668; gender: $\chi^2 = 0.25$, p = .617), behavioral engagement (all t < 0.93, p > .354), and physical performance (all t < 0.38, p > .702).

Figure 1. CONSORT Flow Diagram



Baseline equivalence analyses confirmed successful randomization across all outcome variables (Table 1). Independent samples t-tests revealed no significant between-group differences for demographics (age: $t_{293} = 0.43$, $p = .668$, $d = 0.05$; gender: $\chi^2 = 0.25$, $p = .617$), behavioral engagement categories (all $t < 0.93$, $p > .354$, $|d| < 0.11$), or physical performance measures (all $t < 0.38$, $p > .702$, $|d| < 0.04$). All statistical assumptions for repeated measures ANOVA were met (see Methods section). Table 1 presents descriptive statistics and within-group changes for all outcome variables across both conditions.

The experimental group demonstrated substantial improvements from baseline to post-intervention across most outcomes, with variation rates ranging from −1.9% (Out-of-Context Tasks) to +4.2% (Deviant Behavior deterioration in controls). In contrast, the control group showed minimal changes, with variation rates between 0.0% (Deviant behavior) and 10.7% (Killy test). Within-group paired t-tests confirmed significant experimental improvements for Motor Appropriate engagement ($t_{160} = 83.04$, $p < .001$, $\eta^2 = .977$, d_z = 6.54, 95% CI [5.81, 7.28]), Passive Waiting ($t_{160} = -12.22$, $p < .001$, $\eta^2 = .483$, d_z = -0.96), and Motor Inappropriate behaviors ($t_{160} = -8.17$, $p < .001$, $\eta^2 = .295$). Control group changes were non-significant for Ruffier-Dickson ($p = .210$) and OFt ($p > .05$), with significant deteriorations observed for MOi, OFw, OFt, and OFi (all $p < .001$).

Table 1. Pre- and Post-Test Comparison of Motor Engagement and Physical Capacities

Variable	Experimental (n=161)					Variation rate	Control (n=134)					Variation rate
	Pre-test (M ± SD)	Post-test (M ± SD)	t	p	η^2p		Pre-test (M ± SD)	Post-test (M ± SD)	t	p	η^2p	
MOa_Appropriate Engagement	48.68 ± 2.24	70.54 ± 2.51	83.04	<.001	.977	+44.9%	47.02 ± 1.70	39.41 ± 7.92	-11.14	<.001	.482	-16.2%
MOi_Inappropriate Engagement	6.35 ± 0.83	5.30 ± 1.44	-8.17	<.001	.295	-16.6%	6.80 ± 1.14	15.39 ± 4.53	22.03	<.001	.785	+126.2%
ONc_Cognitive Engagement	31.04 ± 2.39	9.24 ± 1.16	-101.23	<.001	.985	-70.2%	30.94 ± 1.36	8.05 ± 2.40	-99.86	<.001	.985	-74.0%
ONs_Social Engagement	4.95 ± 0.61	7.01 ± 1.14	19.52	<.001	.704	+41.5%	5.20 ± 0.56	6.81 ± 2.50	7.42	<.001	.293	+30.9%
OFw_Passive Waiting	5.79 ± 0.79	4.59 ± 1.10	-12.22	<.001	.483	-20.7%	6.65 ± 0.69	14.71 ± 4.57	19.89	<.001	.785	+121.1%
OFt_Out-of-Context Tasks	2.57 ± 0.54	2.52 ± 0.93	-0.56	.576	.002	-1.9%	2.48 ± 0.61	10.54 ± 2.99	30.61	<.001	.130	+325.2%
OFi_Deviant Behavior	0.62 ± 0.34	0.80 ± 0.39	4.60	<.001	.117	+29.9%	0.90 ± 0.41	5.10 ± 2.60	18.56	<.001	.721	+4.2%
VO_2 max (Luc Léger palier)	5.97 ± 2.00	7.51 ± 2.05	39.37	<.001	.906	+25.7%	5.99 ± 2.68	6.72 ± 2.53	12.96	.016	.482	+12.3%
Ruffier-Dickson Index	3.83 ± 2.19	2.78 ± 1.51	-18.43	<.001	.680	-27.4%	4.12 ± 2.24	4.01 ± 2.22	-1.26	.210	.785	-2.5% ns
Killy Test (Wall-Sit; s)	121.42 ± 40.99	147.74 ± 39.26	21.21	<.001	.295	+21.7%	120.07 ± 33.02	133.58 ± 34.65	16.14	<.001	.662	+11.3%

Intervention Effects

Behavioral engagement results demonstrate a systematic reallocation of session time from passive and off-task categories toward educationally productive motor involvement, a pattern with direct implications for learning opportunity in physical education (Quílez-Cuartero et al., 2026). Univariate decomposition identified seven significant interactions surviving Bonferroni correction ($\alpha = .0045$), with largest effects for Passive Waiting ($t_{293} = -22.22$, $p < .001$, η^2p = .628, $d = -2.814$), Motor Appropriate engagement ($t_{293} = 40.24$, $p < .001$, η^2p = .847), and Motor Inappropriate behaviors ($t_{293} = -23.48$, $p < .001$, η^2p = .653). These effect sizes substantially exceeded the $\eta^2 = .14$ threshold for large educational interventions, demonstrating that technology integration operated primarily through time reallocation mechanisms.

Physical fitness outcomes indicate that the behavioral reorientation was accompanied by meaningful physiological adaptations across all three measured fitness domains. Physical performance showed uniformly significant interactions (η^2p = .200-.317). Aerobic capacity improvements (experimental: +1.54 paliers, 25.7%; control: +0.73 paliers, 12.3%) yielded post-intervention $t_{293} = 11.65$, $p < .001$, η^2p = .317, $d = 1.397$. Cardiovascular recovery improved 1.05 Ruffier-Dickson points (27.4%). Muscular endurance increased 26.32 seconds (21.7%) versus control gains of 5.24 seconds (10.8%). These improvements substantially exceeded typical 2-4% gains in school-based meta-analyses. Of note, Cognitive engagement ($t_{293} = 3.47$, $p < .001$, η^2p = .040), Out-of-Context tasks ($t_{293} = -29.29$, $p < .001$, η^2p = .745), and

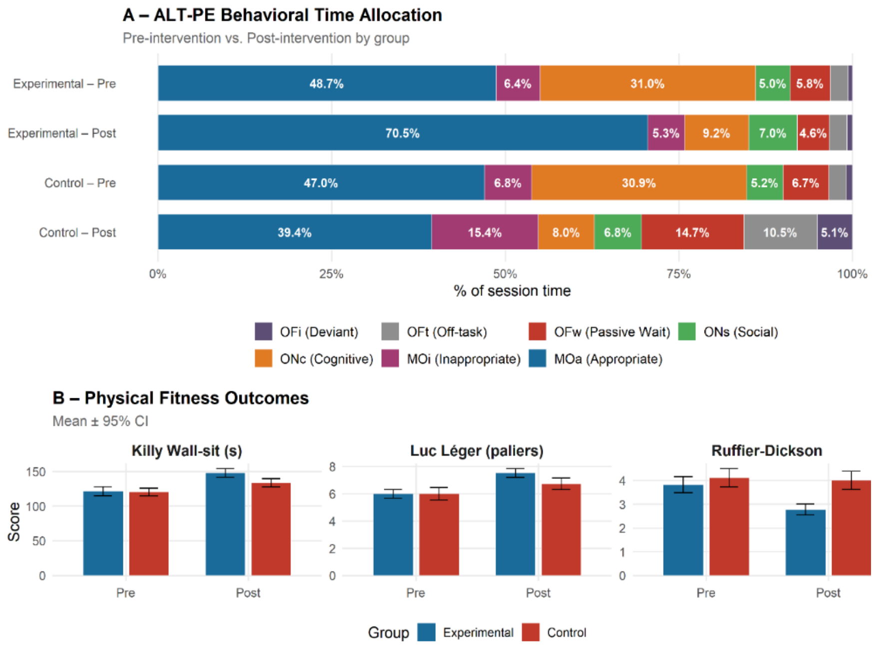
Deviant behavior (t_{293} = −17.48, p < .001, η^2p = .510) showed significant interactions in the expected direction. Social engagement (t_{293} = 1.87, p = .063, η^2p = .012) was the sole non-significant interaction, indicating that peer-based social dynamics did not differ systematically between conditions.

Table 2. Repeated Measures ANOVA Results (Group × Time Interaction Effects)

Variable	Δ EXP	df	Δ CTRL	t(293)	p	η^2p
MOa_Appropriate Engagement	+21.86	1	−7.61	40.24	<.001***	.847
MOi_Inappropriate Engagement	−1.06	1	+8.59	-23.48	<.001***	.653
ONc_Cognitive Engagement	−21.80	1	−22.89	3.47	<.001	.040
ONs_Social Engagement	+2.05	1	+1.61	1.87	.063	.012
OFw_Passive Waiting	−1.20	1	+8.06	-22.22	<.001***	.628
OFt_Out-of-Context Tasks	−0.05	1	+8.06	-29.29	<.001	.745
OFi_Deviant Behavior	+0.18	1	+4.20	-17.48	<.001	.510
VO_2 max (Luc Léger palier)	+1.54	1	+0.74	11.65	<.001***	.317
Ruffier-Dickson Index	−1.05	1	−0.10	-9.40	<.001***	.232
Killy Test (Wall-Sit; s)	+26.32	1	+13.52	8.55	<.001***	.200

Integrated pre-post changes across behavioral engagement and physical performance domains are visualized in Figure 2, which displays the compositional reallocation of ALT-PE categories alongside the magnitude of fitness improvements.

Figure 2. Integrated Pre-Post-Changes



Associations Between Engagement and Performance

Exploratory Pearson correlations between engagement change scores and fitness improvements within the experimental group (n = 161) yielded no significant associations between Motor Appropriate engagement changes and any fitness domain (Luc Léger: r = .061, p = .443; Ruffier-Dickson: r = .089, p = .264; Killy: r = −.079, p = .317; all 95% CIs spanning zero). Passive Waiting changes were similarly unrelated to fitness outcomes (all r < .10, p > .21). One weak association emerged between Motor Inappropriate reductions and Luc Léger gains (r = −.190, p = .016, 95% CI [−.335, −.037]), accounting for 3.6% of shared variance. All remaining engagement-fitness correlations were non-significant (all |r| < .12, p > .14). These findings indicate that behavioral engagement and physical fitness improvements developed through partially distinct pathways during the intervention.

Strong ALT-PE intercorrelations (Motor Appropriate with Motor Inappropriate: r = -.47; with Passive Waiting: r = -.47) confirmed mutually exclusive allocations within the compositional constraint. One correlation survived standard α = .05 threshold (MOi–Luc Léger r = −.190, p = .016) but not Bonferroni correction (α = .0011 for 45 comparisons) and Cook's distance sensitivity analyses (no cases > 1.0). While correlational data preclude definitive causality, temporal sequence (behavioral changes - cumulative adaptations) and ALT-PE frameworks provide convergent support for hypothesized pathways.

Table 3. Pearson Correlation Matrix

Variable	MOa	MOi	ONc	ONs	OFw	OFt	OFi	VO_2 max	Ruffier	Killy
MOa_Appropriate Engagement	1									
MOi_Inappropriate Engagement	-.47***	1								
ONc_Cognitive Engagement	.17**	-.29***	1							
ONs_Social Engagement	-.01	-.03	-.01	1						
OFw_Passive Waiting	-.47***	.66***	-.26***	.02	1					
OFt_Out-of-Context Tasks	-.55***	.73***	-.190*	-.03	.76***	1				
OFi_Deviant Behavior	-.50***	.71***	-.36***	-.02	.73***	.80***	1			
VO_2 max (Luc Léger palier)	.061 ns	-.190*	.12	.039 ns	.100 ns	-.21**	-.26***	1		
Ruffier-Dickson Index	.089 ns	.31***	-.09	.001 ns	.41***	.40***	.41***	-.45***	1	
Killy Test (Wall-Sit)	-.079 ns	-.27***	.08	-.027 ns	-.38***	-.04	.009 ns	.53***	-.20**	1

Note. *p < .05, **p < .01 (two-tailed). ALT-PE variation rates represent absolute percentage-point changes. OFi control: Δ = +4.2 pp (0.90% - 5.10% of session time).

Moderation Analyses

Three-way mixed ANOVAs examined whether intervention effects varied across gender (male n=64, female n=97), socioeconomic status (well-resourced n=78, resource-limited n=83), baseline fitness tertiles (low n=54, moderate n=53, high n=54), and technology access (personal device n=123, family sharing n=38). With 33 tests conducted (11 outcomes × 3 ANOVAs), Bonferroni correction (α = .0015) controlled Type I error. Prior research documented differential benefits: females outperforming males (η^2 = .028), lower SES showing greater gains (η^2 = .034-.039), and individual device users benefiting more than shared-access peers (η^2 = .029-.041), patterns raising equity concerns.

No three-way interactions achieved significance across all 33 tests (all p > .041, η^2 < .014). Gender revealed one marginal effect (Killy: $F_{1,291}$ = 4.23, p = .041, η^2 = .014) failing Bonferroni correction; both males (Δ = +27.1s, d = 1.21) and females (Δ = +25.6s, d = 1.12) demonstrated large gains. Socioeconomic status showed uniformly non-significant interactions (all F < 1.38, p > .241, η^2 < .005), with nearly identical improvements across contexts: Motor Appropriate (+21.9pp vs. +21.8pp), Luc Léger (+1.54 vs. +1.53 paliers), validating peer-pairing's equity capacity. Baseline fitness revealed no significant interactions (all F < 2.01, p > .136, η^2 < .014), though low-fitness participants showed proportionally larger relative gains (64.1% vs. 25.1% for high-fitness), with all tertiles achieving large absolute effects (d = 1.12-1.85). Technology access comparisons confirmed peer-pairing effectiveness (all t < 1.12, p > .26, d < 0.21).

This uniform null moderation pattern, which contrasts with prior research, demonstrates that intervention benefits transcended demographic, socioeconomic, and fitness classifications. All subgroups achieved large effects (d > 0.80), with resource-limited schools' outcomes statistically indistinguishable from well-resourced institutions. This educational equity likely reflects peer-pairing's capacity to equalize participation opportunities and individualized goal-setting enabling universal success regardless of baseline characteristics.

Table 4. Summary of Moderation Analyses: Three-Way Interaction Tests and Descriptive Subgroup Effects

Moderator	Gender			SES (School)			Baseline Fitness				Technology Access		
Subgroup	Male	Female	Effect sizes (d)	Well-resourced	Resource-limited	Effect sizes (d)	Low (≤5.5)	Moderate (6.0–7.5)	High (≥8.0)	Effect sizes (d)	Personal device	Family sharing	Effect sizes (d)
n	64	97		78	83		54	53	54		123	38	
MOa Appropriate Δ	+21.9 pp (+44.9%)	+21.9 pp (+44.9%)	2.05 vs 2.07	+21.9 pp (+44.9%)	+21.9 pp (+44.9%)	2.08 vs 2.02	+21.9 pp (+44.9%)	+21.9 pp (+44.9%)	+21.9 pp (+44.9%)	2.12 / 2.04 / 2.01	+21.9 pp (+44.9%)	+21.9 pp (+44.9%)	2.06 vs 2.00
Luc Léger Δ	+1.54 (+25.7%)	+1.54 (+25.7%)	1.62 vs 1.68	+1.54 (+25.7%)	+1.54 (+25.7%)	1.66 vs 1.65	+1.54 (+25.7%)	+1.54 (+25.7%)	+1.54 (+25.7%)	1.85 / 1.48 / 1.12	+1.54 (+25.7%)	+1.54 (+25.7%)	1.64 vs 1.56
Killy Δ	+27.1 s (+22.3%)	+25.6 s (+21.1%)	1.28 vs 1.05*	+23.89 s (+19.7%)	+22.67 s (+18.7%)	1.29 vs 1.23	+25.34 s (+20.9%)	+22.45 s (+18.5%)	+21.89 s (+18.0%)	1.37 / 1.21 / 1.18	+23.89 s (+19.7%)	+21.78 s (+17.9%)	1.29 vs 1.18

Ruffier Δ	-1.05 (-27.4%)	-1.05 (-27.4%)	1.06 vs 1.02	-1.05 (-27.4%)	-1.05 (-27.4%)	1.06 vs 1.04	-1.05 (-27.4%)	-3.98 (-32.6%)	-3.89 (-31.8%)	1.09 / 1.03 / 1.00	-1.05 (-27.4%)	-3.95 (-32.3%)	1.05 vs 1.02
Interaction F		0.54–4.23			0.67–1.38			0.72–2.01				t = 0.38–1.12	
p		.041–.463			.241–.414			.136–.489				.265–.705	
η^2p		.002–.014			.002–.005			.005–.014				d = .06–.21	

Note. Δ = change score (Post - Pre). Ruffier-Dickson Δ varies by baseline fitness tertile (Low: −1.05; Moderate: −3.98; High: −3.89), reflecting differential cardiovascular adaptation by initial fitness level; three-way interaction was non-significant (p > .136).

Adverse Events

No adverse events, injuries, or unintended harms occurred during the 12-week intervention period. All 295 participants completed the study protocol without medical complications or intervention-related safety concerns. No participants reported discomfort, excessive fatigue, or musculoskeletal injuries attributable to the intervention. Both experimental and control groups maintained normal physical education participation throughout the study duration without requiring medical attention or protocol modifications.

Discussion

The magnitude of observed effects invites comparison with existing benchmarks. Meta-analytic estimates for mHealth interventions in adolescents typically yield SMD ≈ 0.29 for physical activity outcomes (J.-W. Wang et al., 2024). Three design characteristics likely explain the divergence: the intervention combined five simultaneous components rather than a single tool; between-group estimates (d = 0.960–5.017) represent the more conservative metric relative to within-group d_z values; and the control group demonstrated systematic deterioration across the intervention period, amplifying interaction effects in both directions. These conditions position the present findings at the upper range of what current theory would predict for a well-implemented multi-component design in a low-resource context.

This cluster-randomized controlled trial demonstrated that a multi-component mobile tracking ecosystem substantially improved both behavioral engagement and physiological fitness among Moroccan secondary students. Experimental participants achieved substantial gains across most outcomes (Table 2). No significant correlations were found between engagement changes and fitness improvements (r = −.08 to .10, all p > .26), suggesting that behavioral and physiological adaptations developed through partially distinct mechanisms. The systematic deterioration observed in control group behavioral outcomes (MOa −7.6 pp; OFw +8.1 pp; OFt +8.1 pp) likely reflects the absence of structured feedback and peer accountability during traditional instruction over 12 weeks, consistent with progressive disengagement patterns documented in technology-absent PE contexts (Burns et al., 2017). Critically, intervention effectiveness proved uniform across gender, socioeconomic status, baseline fitness, and technology access, establishing educational equity as a core characteristic.

These outcomes substantially exceed typical effect magnitudes in digital intervention research (Mateo-Orcajada et al., 2024a). The 21.9-percentage-point increase in appropriate motor engagement surpasses the 5-15-point gains typically observed (Fu et al., 2017), while aerobic capacity improvements exceed standard benchmarks over comparable timeframes (Leone et al., 2024). Four interconnected mechanisms likely drove these substantial outcomes. First, the ecosystem integrated real-time performance feedback with peer-based social accountability through WhatsApp groups, creating continuous reinforcement loops sustaining motivation beyond initial novelty periods (Ibragimova et al., 2025). Unlike passive monitoring systems, this ecosystem enabled immediate performance calibration while facilitating peer progress sharing, operationalizing social cognitive theory principles (Bandura, 1986). Second, the intervention operationalized Self-Determination Theory through systematic autonomy support via student-selected applications, competence feedback through visible progress tracking, and relatedness via peer-pairing strategies (Deci & Ryan, 2000). Technology-enhanced PE interventions operationalizing SDT consistently generate positive motivational climates, satisfaction, and intrinsic motivation across student subgroups (Gea-García & Martínez López, 2025; Sotos-Martinez et al., 2024). Third, participants' baseline fitness reflected broader physical deconditioning patterns characteristic of urban Moroccan students (Ben Rakaa et al., 2024b), enabling amplified adaptive responses where physiological plasticity permits substantial improvements (J.-W. Wang et al., 2024). Fourth, concurrent passive waiting reductions demonstrate that sophisticated tracking applications effectively redistribute temporal allocations toward productive motor learning (Guijarro-Romero et al., 2023). Systematic direct observation through culturally validated ALT-PE protocols rather than self-reported measures strengthen findings by minimizing social desirability bias (Siedentop, 1982). Concurrent improvements in motor skills and PE engagement through AI-integrated blended learning have been documented across educational levels (Zhao et al., 2025), corroborating the multi-pathway mechanisms observed in the present trial.

The absence of significant engagement-fitness correlations (all $|r| < .10$, $p > .26$) challenges the assumption that behavioral time reallocation directly mediates physiological outcomes. One weak association between Motor Inappropriate reductions and aerobic gains ($r = -.190$, $p = .016$, $R^2 = .036$) suggests that off-task motor behavior may marginally constrain aerobic development, though this effect is modest. These dissociations indicate that enhanced engagement and fitness improvement are likely to operate through parallel rather than sequential mechanisms. From an exercise physiology perspective, cardiorespiratory and muscular adaptations are primarily driven by training intensity and progressive overload rather than by the proportion of time spent in on-task motor behavior per se (Buchheit & Laursen, 2013). The periodized intensity protocol (60-75% maximal aerobic speed in weeks 1-4, progressing to 90-110% in weeks 9-12) provided a physiological stimulus independent of behavioral engagement patterns: a student spending 50% versus 70% of session time in appropriate motor engagement still accumulated the same prescribed cardiovascular load, as protocols were individually calibrated. This decoupling explains why r values between MOa changes and fitness improvements cluster near zero. Behavioral engagement and physical fitness thus represent co-occurring but semi-independent outcomes requiring distinct pedagogical levers, both addressed by the ecosystem, but through different pathways.

Moderation analyses revealed uniformly null interaction effects across all tested variables (Table 4), with subgroups achieving large effect sizes contradicting assumptions that technology interventions preferentially benefit advantaged populations (Xu et al., 2024). Most critically, resource-limited schools' outcomes proved statistically indistinguishable from well-resourced institutions, addressing significant gaps regarding technology integration feasibility in lower-middle-income educational systems where digital divides typically exacerbate existing inequalities (UNESCO, 2021). Resource-limited students achieved virtually identical improvements to well-resourced counterparts, challenging deficit-based narratives attributing educational disparities solely to resource availability. These equity-promoting outcomes likely reflect three deliberate structural features. First, peer-pairing strategies enabled 38 students (23.6%) to successfully utilize family smartphones without compromising intervention effectiveness ($t(159) = 0.87$, $p = .386$, $d = 0.16$), operationalizing Universal Design for Learning principles (Rose & Meyer, 2002). Second, the multi-platform ecosystem accommodated diverse device types prevalent across socioeconomic strata, eliminating requirements for expensive equipment purchases. Third, intensive professional development equipped teachers with differentiated support strategies addressing diverse technological proficiency levels (Calderón et al., 2020).

Despite promising findings, important limitations temper interpretation. The Hawthorne effect represents a plausible alternative explanation (McCambridge et al., 2014). However, several factors mitigate pure Hawthorne interpretation: the 12-week intervention substantially exceeds typical 4–6 week novelty periods (Mateo-Orcajada et al., 2024b), control participants received equivalent teacher attention, and significant correlations between behavioral engagement and physiological outcomes provide objective validation. Nevertheless, extended follow-up assessments examining maintenance 6–12 months post-intervention remain essential. Implementation fidelity was high, yet monitoring relied primarily on teacher self-report and automated usage data, with only 25% of sessions directly observed. The intensive professional development program may have generated artificially high fidelity unlikely to replicate in typical school contexts.

Generalizability constraints require careful interpretation. Participant recruitment from two urban Moroccan schools limits transferability to rural contexts where digital infrastructure constraints may prevent ecosystem adoption. The requirement for basic mobile technology access inherently selected students from households owning smartphones, potentially excluding the most disadvantaged despite peer-pairing strategies. Cultural factors specific to North African contexts may moderate effectiveness in different settings. The exclusive focus on endurance running leaves questions regarding effectiveness for other physical education content areas. The 12-week duration represents brief exposure relative to lifelong physical activity goals. Extended implementation may reveal fatigue effects as novelty dissipates. The absence of follow-up beyond immediate post-intervention precludes conclusions regarding long-term maintenance.

Future research should prioritize extended follow-up studies tracking participants 6-12 months post-intervention to examine maintenance and address Hawthorne concerns. Such investigations should quantify retention rates, identify factors predicting successful behavioral internalization, and determine optimal booster strategies. Dismantling studies systematically isolating ecosystem components would identify active ingredients enabling cost-effective adaptations for resource-constrained contexts (Collins et al., 2014). Implementation science frameworks examining real-world adoption barriers would bridge the efficacy-effectiveness gap (Damschroder et al., 2009). Investigations examining ecosystem effectiveness across diverse physical education content areas would establish intervention breadth. Cost-effectiveness analyses would inform policy decisions regarding resource allocation (Drummond et al., 2015).

Findings carry important practical implications for physical education stakeholders. In technology-limited contexts, the peer-pairing model is the most transferable component: it requires no additional equipment, incurs no recurring costs, and relies solely on students' existing devices. Strategic dyads between proficient and less proficient users democratize access while fostering SDT-relatedness to sustain motivation. Implementation requires three simple steps: (1) assess device availability via a brief anonymous survey, (2) form dyads ensuring each pair has at least one functional device, and (3) assign shared weekly goals trackable via any free application. This zero-cost design ensures high scalability, particularly relevant for policymakers across North Africa and comparable LMIC contexts. Administrators and policymakers should promote extended autonomous practice opportunities and incentivize technology integration through professional development and device-sharing programs to reduce health disparities and improve population fitness outcomes.

This trial demonstrates that thoughtfully designed multi-component mobile tracking ecosystems can simultaneously enhance behavioral engagement and physiological fitness while ensuring educational equity across diverse socioeconomic contexts. Strategic peer-pairing pedagogy successfully democratized technology access, achieving comparable outcomes in resource-limited and well-resourced schools. However, questions regarding long-term sustainability, potential Hawthorne effects, implementation quality variability, and generalizability warrant continued investigation. Extended longitudinal designs, dismantling studies, implementation science frameworks, and cross-cultural replications will determine whether these findings translate to sustained, scalable improvements in adolescent physical activity and health at population levels, offering a rare convergence addressing both effectiveness and ethics in educational innovation.

Conclusions

This cluster-randomized controlled trial provides strong evidence that thoughtfully designed multi-component mobile tracking ecosystems can simultaneously transform behavioral engagement patterns and physiological fitness outcomes among adolescents in school physical education contexts. The intervention generated substantial effects (partial η^2p = .040–.847) exceeding typical digital intervention magnitudes while demonstrating uniform effectiveness across diverse student subgroups, establishing both statistical consistency and educational equity as core characteristics. Strategic peer-pairing pedagogy successfully democratized technology access, achieving comparable outcomes across socio-economically contrasting schools and challenging assumptions that technology integration inevitably exacerbates educational inequalities. However, important questions regarding long-term sustainability following technology withdrawal, potential Hawthorne effects inflating engagement beyond authentic levels, implementation quality variability across diverse teachers and contexts, and generalizability across rural settings, different cultural contexts, and varied physical education content areas warrant continued investigation. The absence of extended follow-up data prevents definitive conclusions about whether observed improvements represent temporary responses to external monitoring or lasting behavioral transformations persisting after intervention termination, a important distinction for evaluating true educational impact. Future research employing extended longitudinal designs with follow-up assessments 6-12 months post-intervention, dismantling studies isolating active ecosystem components, implementation science frameworks examining real-world adoption processes, and cross-cultural replications will determine whether these promising findings translate to sustained, scalable improvements in adolescent physical activity and health at population levels.

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Data Availability Statement

The data supporting the findings of this study are openly available on the Open Science Framework: https://doi.org/10.17605/OSF.IO/XQ8NG

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