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Integrated smart relay baton and multisensor wearable system

Cahyo Yuwono[1], Adi S[1], Pangondian Hotliber Purba[2], Himmatul Ulya[1], Vina Oktaviani[3], Tommy Soenyoto[1], Erna Setyowati[1], Bondan Fiqi Riyalda[4], Sri Indah Ihsani[3], Made Bang Redy Utama[3], Bambang Priyono[1], Khoiril Anam[1], Laily Mita Andriana[5], Mahenderan Appukutty[6], Dewangga Yudhistira[5]
[1]Universitas Negeri Semarang, Indonesia
[2]Universitas Negeri Medan, Indonesia
[3]Universitas Negeri Jakarta, Indonesia
[4]Badan Riset dan Inovasi Nasional, Indonesia
[5]Universitas Negeri Surabaya, Indonesia
[6]Universiti Teknologi MARA, Malaysia
*Corresponding Author: cahyoyuwono@mail.unnes.ac.id

ABSTRACT

Relay sprint performance is influenced by the efficiency and synchronization of baton exchanges, yet current evaluation methods remain largely subjective and fragmented. This study aimed to develop and evaluate an integrated Smart Relay Baton and multisensor wearable system for objective and real-time assessment of relay performance. A research and development approach based on the Borg–Gall model was employed, followed by a quasi-experimental pre–post design involving 241 sprint relay athletes. The system integrated accelerometer-based motion tracking within the baton and physiological monitoring through wearable sensors and smartwatch support, with synchronized data transmission via an MQTT-based IoT architecture. Key variables included transition time, entry speed, average acceleration, synchronization delay, heart rate response, rating of perceived exertion (RPE), and the Relay Performance and Orchestration Index (RPOI). Results showed pre–post changes in transition time (Cohen's dz = −0.82), synchronization delay (dz = −0.74), entry speed (dz = 0.74), average acceleration (dz = 0.48), and RPOI (dz = 1.05). Heart rate during the exchange showed a small reduction (dz = −0.32), while 60-s heart rate recovery increased (dz = 0.54) and RPE decreased (dz = −0.75). These findings indicate that the integrated system can provide comprehensive, data-driven information on baton exchange and relay performance by combining movement and physiological measures. However, the observed changes represent within-participant differences and should not be interpreted as evidence of a causal effect of the system or as evidence of pedagogical effectiveness.

Keywords: relay baton, internet of things, multisensor wearable, performance orchestration, sports science

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INTRODUCTION

Effective relay performance depends not only on individual sprint ability but also on the quality of baton exchange, where small temporal errors between incoming and outgoing runners can result in substantial losses of velocity and transition efficiency. In physical education and sport coaching contexts, this exchange phase represents an important instructional problem because athletes must simultaneously regulate running speed, movement timing, spatial positioning, and baton transfer. Individualized training enhances athletic performance and talent development, thereby facilitating future improvements in athleticism (Yuwono, Billiandri, et al.,

2025). Optimal baton-passing techniques are essential for success in relay races (Radford & Ward-Smith, 2003). However, conventional batons neglect ergonomic considerations and measurement requirements (Griffin et al., 2021). They function merely as passive tools, failing to provide quantitative metrics on speed, acceleration, rhythm, and synchronization during baton exchanges. This absence of reliable statistical data hampers coaches' ability to objectively evaluate athletes, identify team weaknesses, and determine optimal runner sequencing. As a result, performance assessment relies heavily on aggregate race times and subjective observation, which provides limited information about the micro-temporal characteristics of the exchange and makes it difficult for learners and coaches to identify whether performance errors originate from entry speed, acceleration, or inter-runner timing. Objectives and immediate feedback are therefore needed to support more evidence-informed learning and training in relay skills.

Innovations in relay baton design are essential for achieving peak performance (Kusuma et al., 2023; Yuwono et al., 2024). Modified batons offer enhanced safety, comfort, and precision compared to conventional ones (Hidayatullah et al., 2020; Shandal, 2022). Moreover, timeliness is crucial for deriving insights from data (Johnston & Baker, 2022). The integration of 5G IoT technology and accelerometer sensors offers a novel solution for obtaining real-time data, improving evaluation processes (Wang & Zhao, 2021).

Wearable multisensor systems further contribute to performance monitoring by capturing acceleration patterns (Sheerin et al., 2020; Tenforde et al., 2020), movement dynamics (Lariviere et al., 2020), and even predicting locomotion speed through raw data analysis (Davis et al., 2023). Recent wearable frameworks incorporate inertial measurement units (IMUs), surface electromyography (sEMG), and physiological sensors to monitor hydration, heart rate, neuromuscular activity, and fatigue responses in real time (Du, 2024; Kim et al., 2024). The application of artificial intelligence and machine learning enhances synchronized data processing, enabling biomechanical load quantification and injury prevention strategies (Bastiaansen et al., 2022; Phatak et al., 2021).

Despite these advancements, existing technologies primarily focus on individual running analysis and do not integrate biomechanical exchange variables with physiological responses within a synchronized relay context. Bibliometric mapping of relay-related publications (2020-2025) further reveals that research remains fragmented, dominated by isolated biomechanical or technological investigations without integrated real-time orchestration systems. Contributions from Southeast Asia are particularly limited, and few studies explicitly address relay-specific exchange dynamics in competitive environments.

An important distinction must also be made between the present study and the authors' previous (Yuwono, Adi, et al., 2025). The 2025 study focused on the development and educational evaluation of an accelerometer-based Smart IoT Relay Baton for measuring relay performance variables such as transition time, entry speed, acceleration, and coordination. The current study extends this earlier work rather than simply reproducing it by integrating the baton-derived biomechanical measurements with multisensor wearable physiological monitoring and smartwatch-supported heart-rate data within a synchronized IoT architecture. In addition, the present study introduces the Relay Performance Orchestration Index (RPOI), which combines entry velocity, acceleration, and synchronization-related information. Thus, the research shifts from the development and educational evaluation of a smart baton toward an integrated analysis of relay performance orchestration.

To address this gap, this research proposes an innovative smart relay baton system incorporating embedded inertial sensing and IoT-enabled multisensor synchronization to objectively quantify micro-temporal exchange performance and inter-runner coordination. Rather than evaluating the baton as a standalone technological device, the present study examines the integrated system as a multidimensional assessment framework that combines biomechanical and physiological information during the relay exchange. By integrating biomechanical exchange variables with physiological responses in real time, the system is intended to provide a data-driven basis for examining individualized sprint relay performance, team coordination, and exchange efficiency.

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Accordingly, the study addresses the following research question: How do relay performance, physiological, perceived-exertion, and RPOI measures change between the conventional-baton and Smart Relay Baton conditions? The study was guided by the expectation that the Smart Relay Baton condition would be associated with lower transition time and synchronization delay and higher entry speed, acceleration, and RPOI.

METHOD

Research design

This study employed a Research and Development (R&D) framework adapted from the Borg and Gall model, integrating technological prototyping with experimental performance evaluation. The development phase included needs analysis, system architecture design, expert validation, iterative refinement, and field implementation. The evaluation phase applied a quasi-experimental pre-post design to assess the changes in relay exchange performance associated with implementation of the integrated Smart Relay Baton and multisensor wearable system under standardized training conditions. The study was structured to examine both the technological performance of the system and its application as an objective assessment and feedback tool for relay training.

The study followed a sequential development and evaluation process consisting of: (1) needs and performance-assessment analysis; (2) hardware and software system design; (3) prototype development; (4) technical and content review by experts; (5) pilot testing and refinement; (6) field implementation; (7) synchronized data acquisition; and (8) statistical evaluation of pre-post-performance. This sample size provided adequate statistical power for detecting moderate effect sizes in paired comparisons.

Ethical considerations

The study was approved by the Institutional Research Ethics Committee of Universitas Negeri Semarang (Approval No. B/6430/UN37.3.1/KEP.00/2026). All procedures were conducted in accordance with the principles of the Declaration of Helsinki. Written informed consent was obtained from all participants before data collection.

Participants

A total of 241 sprint relay athletes (n = 241) from the Indonesian Athletics Federation (PASI) Central Java participated. Purposive sampling was applied with inclusion criteria: age 19-23 years, provincial-level competition experience, and regular training frequency (≥3 sessions per week). Athletes with acute injuries or medical contraindications were excluded. This sample size provided adequate statistical power for detecting moderate effect sizes in paired comparisons. Participant characteristics are summarized in Table 1.

Table 1. Participant characteristics (n=241)

Variable	Total (n=241)	Male (n=121)	Female (n=120)
Age (years), mean ± SD	19.3 ± 2.4	19.5 ± 2.5	19.1 ± 2.3
Height (cm), mean ± SD	170.6 ± 8.1	174.8 ± 6.9	166.2 ± 6.7
Weight (kg), mean ± SD	62.9 ± 9.8	68.1 ± 8.2	57.7 ± 7.5
Training experience (years), mean ± SD	3.8 ± 1.9	4.0 ± 1.8	3.6 ± 2.0
Event specialization, n (%)			
- 4×100 m	181 (75%)	92 (76%)	89 (74%)
- 4×400 m	60 (25%)	29 (24%)	31 (26%)
Preferred handover hand (R/L), n (%)	197 / 44	104 / 17	93 / 27
Recent injury (last 6 months), n (%)	38 (15.8%)	20 (16.5%)	18 (15.0%)

The analytical dataset consisted of synchronized biomechanical, physiological, and perceived-exertion observations collected during relay exchange trials. Biomechanical data originated from the embedded accelerometer in the Smart Relay Baton, while physiological data

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were obtained from the multisensor wearable system and smartwatch-supported heart-rate monitoring. The primary unit of analysis was the athlete-level observation.

To preserve data provenance, each observation was assigned a unique participant and trial identifier. Baton, wearable, and smartwatch measurements were time-synchronized before analysis, allowing observations from the exchange phase to be linked across sensing modalities. Raw sensor observations were retained before preprocessing, while processed variables were used for statistical analysis.

The study included 121 male and 120 female athletes. Event specialization comprised 181 athletes in the 4 × 100-m event and 60 athletes in the 4 × 400-m event.

Instruments

The primary instrument was an integrated Smart IoT Relay Baton system consisting of smart relay Baton components and wearable multisensory band. The smart relay Baton components consist of MPU-6050 accelerometer, WEMOS D1 ESP8266 microcontroller, SIM800L communication module, 7.4V 18650 battery (5000 mAh), and RGB LED feedback indicator. Then, the wearable multisensor band consist of Heart rate sensor and Physiological load monitoring module.

Data were transmitted in real time via MQTT-based IoT architecture to a web-based dashboard supported by PHP backend and MySQL database. The system enabled synchronized capture of biomechanical and physiological data during exchange phases.

A smartwatch was used to complement physiological monitoring for real-time heart rate tracking. The sensing architecture was organized into three data streams: (1) baton-based inertial measurements representing movement during the exchange, (2) wearable physiological measurements representing internal response, and (3) smartwatch heart-rate measurements providing complementary physiological monitoring. The MQTT communication layer was used to transmit sensor observations to the server, where records were time-stamped and stored for subsequent processing.

Device technical verification and field feasibility

Before field implementation, the integrated Smart Relay Baton and multisensor wearable system underwent technical verification and field-feasibility assessment to evaluate operational stability, repeated-measure consistency, synchronization integrity, and real-time data-transmission performance during relay-specific exchange trials. The verification procedures were conducted under repeated baton-exchange conditions designed to reproduce the rapid acceleration, deceleration, directional changes, and handover movements characteristic of the relay exchange zone.

Prior to each testing session, the MPU-6050 inertial sensor was initialized and examined for baseline stability. The verification procedure included zero-offset checking, orientation consistency assessment, and confirmation of continuous signal acquisition before athletes commenced the exchange trials. Repeated exchange recordings were subsequently examined to determine whether the system consistently captured temporally coherent movement patterns and preserved the expected order of exchange-related events across comparable trials. These procedures were intended to verify the system's operational capacity to identify and time-stamp relay-specific movement events, rather than to establish criterion-level accuracy for absolute acceleration values.

The integrated system generated three synchronized data streams: baton-based inertial data, wearable physiological data, and smartwatch-supported heart-rate data. Synchronization integrity was assessed through time-stamp alignment of records across the three streams before storage and analysis. The MQTT communication layer was evaluated by comparing locally generated sensor records with time-stamped records received by the server and stored in the MySQL database. Technical observations included continuity of data acquisition, successful record reception, temporal ordering of sensor events, delayed transmission, connection interruptions, device-reset events, and the presence of missing or incomplete records.

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The field-feasibility assessment focused on the capacity of the system to maintain data capture throughout the relay exchange sequence and to provide interpretable feedback for subsequent training adjustments. Accordingly, the system was evaluated as operationally feasible when sensor recording remained continuous during the exchange phase, the expected event sequence could be reconstructed from the synchronized time-stamped records, and the dashboard displayed exchange-related variables in a form usable by athletes and coaches. This assessment supports the use of the integrated system as a practical monitoring and feedback platform within relay-training settings; it does not claim equivalence with laboratory-grade motion capture or ECG-based physiological instrumentation.

Heart-rate values obtained from the wearable and smartwatch were used as complementary physiological indicators of exercise response during the exchange trials. As the present field implementation did not include a simultaneous comparison with an ECG-based monitor or independently validated chest-strap criterion device, heart-rate outcomes were interpreted as within-system supportive indicators rather than as independently criterion-validated clinical measures. This distinction is important because rigorous wearable heart-rate validation generally requires comparison against an appropriate reference device and agreement analyses such as Bland Altman limits of agreement and MAPE (Argent et al., 2022).

Usability and field applicability were additionally reviewed by sport-technology experts and PASI coaches through structured feedback. The review addressed ease of device operation, baton handling comfort, wearable attachment, perceived interference with running technique, battery practicality, data-transmission stability, dashboard readability, interpretability of transition-time and synchronization feedback, and suitability for routine relay training. Expert and coach feedback informed final refinement of device-placement procedures, feedback presentation, and field implementation protocols before the main performance evaluation.

Trial protocol

Baseline assessment was conducted using a conventional relay baton before implementation of the integrated Smart IoT Relay Baton and multisensor wearable system. Subsequently, the same athletes completed an equivalent post-implementation assessment using the Smart Relay Baton under standardized training and environmental conditions. The conventional baton condition served as the pre-implementation condition, whereas the Smart Relay Baton condition represented the post-implementation condition. This within-participant procedure was intended to examine changes in relay-exchange performance while maintaining consistency in the running task.

To minimize procedural variation, relay composition, runner order, handover technique, exchange-zone location, running direction, and starting marks were maintained across the pre- and post-implementation conditions. Athletes completed the same standardized warm-up before every test session, consisting of low-intensity running, dynamic mobility exercises, sprint-specific drills, and progressive accelerations. No maximal relay-exchange trial began until athletes had completed the standardized preparation procedure.

During each trial, the incoming runner approached the exchange zone at the prescribed running intensity while the outgoing runner-initiated acceleration from an individualized check mark. The outgoing runner accelerated through the designated acceleration area and received the baton within the official exchange zone. Following the handover, the outgoing runner continued running beyond the exchange zone to preserve a realistic velocity-transfer pattern. Sensor acquisition was initiated before the incoming runner entered the exchange area and was maintained throughout the complete exchange sequence. The integrated system simultaneously recorded baton-derived inertial data, wearable physiological data, smartwatch-supported heart-rate data, and time-stamped transmission records.

Each relay unit performed five exchange-phase repetitions in each condition, with a standardized passive recovery interval of 3 min between trials. This recovery interval was applied to minimize acute fatigue and maintain the quality of sprint mechanics, baton handling, and inter-runner coordination across repeated exchange attempts. The repeated-trial procedure was intended to provide stable measurements of transition time, entry speed, acceleration,

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synchronization delay, and physiological responses while retaining relay-specific movement characteristics.

Trials were conducted on a 400-m outdoor synthetic athletics track using the same lane allocation and track surface for both conditions. Testing was scheduled in two standardized daily sessions: a morning session from 07:00 to 09:00 and an afternoon session from 16:00 to 18:00. Each relay unit was assessed within the same session period across pre- and post-implementation conditions whenever feasible, thereby reducing potential variation associated with diurnal changes in physical readiness and environmental conditions. Ambient temperature, weather conditions, wind conditions, and track-surface status were recorded before each session. Trials were postponed or rescheduled in the event of rain, unsafe track-surface conditions, or wind conditions judged likely to materially affect sprint performance.

To reduce carry-over effects, athletes received standardized verbal instructions across all trials, and feedback was limited according to the assigned study phase. During baseline trials, athletes performed the exchange according to their usual relay-training procedure without real-time system feedback. During the Smart Relay Baton condition, the integrated system captured synchronized data and provided the planned feedback through the web-based dashboard and RGB indicator according to the standardized feedback protocol. All completed trials were reviewed for recording completeness, successful baton transfer, compliance with the designated exchange zone, and synchronization of sensor records before inclusion in the analytical dataset.

Feedback protocol

The integrated Smart Relay Baton and multisensor wearable system provided real-time performance information through a web-based dashboard and an RGB LED feedback mechanism. The dashboard displayed time-stamped exchange data, whereas the RGB LED provided immediate field-level visual feedback during and immediately after baton-transfer attempts. Feedback focuses on measurable exchange characteristics, including transition time, entry speed, average acceleration, synchronization delay, heart-rate response, and the Relay Performance Orchestration Index (RPOI). The purpose of this feedback was to make otherwise difficult-to-observe temporal and coordination characteristics visible to athletes and coaches, thereby supporting evidence-informed adjustment of relay-exchange technique during training.

Immediately after each exchange-phase trial, athletes and coaches reviewed the dashboard output for transition time, entry speed, acceleration, synchronization delay, and successful completion of the baton handover. The RGB LED provided an immediate visual indication of system status and exchange-event detection, while the dashboard enabled more detailed review of the recorded performance variables. After every set of five repetitions, the coach and relay unit received a brief standardized feedback discussion based on the displayed values and their changes across trials. The discussion focused on identifying whether subsequent adjustments should prioritize the outgoing runner's acceleration timing, the incoming runner's approach velocity, the placement and timing of the receiving hand, or the temporal synchronization between runners.

Athletes were instructed to use feedback to make targeted adjustments in subsequent trials. For example, when synchronization delay was prolonged, athletes were instructed to review the outgoing runner's check mark and initiation timing. When transition time was prolonged despite adequate entry speed, coaching feedback focused on hand position, baton-placement accuracy, and the continuity of the receiving runner's acceleration. When entry speed was reduced, the incoming runner was instructed to maintain sprint velocity into the exchange zone while the outgoing runner adjusted acceleration progression to match the incoming runner's approach. These instructions were applied consistently across relay units to minimize variation in coaching exposure and ensure that performance changes were associated with the standardized feedback process.

The feedback-supported intervention was delivered over four weeks, with three relay-training sessions per week. Each session included approximately 30 min of feedback-supported relay-exchange practice after the standardized warm-up. All relay units received the same feedback variables, the same dashboard display format, and the same standardized coaching

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instructions. The intervention was therefore designed to support progressive refinement of exchange coordination rather than simply providing descriptive performance information.

At the end of each session, coaches reviewed the relay unit's overall performance pattern, including changes in transition time, entry speed, synchronization delay, and RPOI across repeated trials. This session-level review was used to guide subsequent training emphasis while preserving the standardized structure of the intervention.

Procedure

Baseline trials were conducted using conventional relay batons. Subsequently, identical trials were performed using the Smart IoT Relay Baton under standardized environmental and training conditions.

Each relay unit completed multiple exchange-phase repetitions to ensure stability of measurement. Performance variables recorded included Transition time, Entry speed into the exchange zone, Average acceleration, Synchronization delay (inter-runner temporal offset), and Heart rate response.

This design enabled within-subject comparison of coordination dynamics and physiological responses. Performance variables and index construction, velocity was calculated as (1).

$$v = s / t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

and the equation of acceleration as (2)

$$a = \Delta v / \Delta t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

The equation of exchange time loss as (3)

$$\Delta t_loss = t_actual - t_ideal \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3)$$

The Relay Performance and Orchestration Index (RPOI) was constructed as a study-specific composite indicator combining entry speed, average acceleration, and synchronization delay. Before aggregation, the three component variables were transformed to standardized scores using the pooled pre–post distribution. Entry speed and average acceleration were treated as performance-positive components, whereas synchronization delay was reverse-coded so that higher values consistently represented more favorable relay-exchange performance. Equal weighting was applied to the three components ($w_1 = w_2 = w_3 = 1/3$). The standardized RPOI was then linearly transformed to a 0–10 scale for ease of interpretation. The RPOI was used as a relative, sample-based indicator and was not considered and independently validated universal performance scale. The formula as (4).

$$RPOI_{raw} = \frac{1}{3}Z_{entry\ speed} + \frac{1}{3}Z_{acceleration} - \frac{1}{3}Z_{synchronization\ delay} \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (4)$$

where Zdenotes the standardized score based on the pooled pre–post distribution. The synchronization-delay component is subtracted because lower synchronization delay represents better temporal coordination. Then:

$$RPOI_{0-10} = 10 \times \frac{RPOI_{raw} - RPOI_{min}}{RPOI_{max} - RPOI_{min}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (5)$$

Sensor data processing

Raw sensor data from the Smart Relay Baton, multisensor wearable, and smartwatch were exported from the MQTT-enabled database and synchronized using their recorded timestamps. Synchronization was performed before variable extraction to ensure that biomechanical and physiological observations corresponded to the same relay-exchange attempt. Each record was linked to a unique participant identifier, relay-unit identifier, trial identifier, condition, and sensor timestamp.

The relay-exchange window was defined as the interval beginning when the incoming runner entered the designated exchange area and ending when the baton transfer had been completed and stable control of the baton had been established by the outgoing runner. Exchange-

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window boundaries were identified from the time-stamped baton sensor signal in conjunction with the trial protocol and recorded event sequence. Records outside this interval were retained in the raw dataset but were not used for exchange-phase variable calculation.

Before variable extraction, tri-axial accelerometer signals were inspected for non-physiological spikes, signal saturation, repeated timestamps, abrupt discontinuities, and missing sampling intervals. The effective sampling frequency was determined from the timestamps recorded by the sensor system. Records that did not meet the predefined data-quality criteria were flagged and excluded from the corresponding variable calculation. No data were imputed.

The resultant acceleration magnitude was calculated from the three orthogonal accelerometer axes as (6).

$$A_{res} = \sqrt{a_x^2 + a_y^2 + a_z^2} \quad \text{..... (6)}$$

where a_x, a_y, and $a_z$represent acceleration recorded along the three sensor axes. Average acceleration was calculated as the mean processed acceleration value within the defined exchange window.

Entry speed was operationalized as the estimated approach velocity of the incoming runner at entry into the exchange zone. Where a distance–time procedure was used, entry speed was calculated as (7)

$$v = \frac{d}{t} \quad \text{..... (7)}$$

where d represents the predefined approach distance and $t$represents the time required to traverse that distance. Entry speed was interpreted as a field-based performance indicator rather than a laboratory-grade direct measurement of running velocity. Acceleration was calculated as (8).

$$a = \frac{\Delta v}{\Delta t} \quad \text{..... (8)}$$

where Δvrepresents the change in velocity and Δtrepresents the corresponding time interval. Synchronization delay was defined as the temporal difference between the predefined incoming-runner event and the corresponding outgoing-runner acceleration or handover event. Transition time was defined as the duration from the onset of the exchange sequence to completed baton transfer based on the pre-specified sensor-event criteria.

Heart rate during the exchange was calculated as the mean heart rate recorded within the exchange window. Heart-rate recovery was calculated as the reduction in heart rate from the immediate post-exchange value to the value obtained 60 s after trial completion. Rating of perceived exertion (RPE) was recorded using the 0–10 scale immediately after each trial according to the standardized trial procedure.

Missing or corrupted records were identified using predefined quality-control criteria, including missing timestamps, duplicate records, signal saturation outside the configured sensor range, non-physiological spikes, incomplete exchange-window coverage, and failure of sensor-to-server transmission. No data imputation was performed. Valid repeated trials were retained, and participant-level values for each condition were calculated as the mean of valid trial-level observations.

Data analysis

All statistical analyses were conducted using IBM SPSS Statistics for Windows, Version 26.0 (IBM Corp., Armonk, NY, USA). Descriptive statistics for continuous variables were presented as mean ± standard deviation (SD), whereas categorical variables were summarized as frequencies and percentages. The distribution of continuous outcome variables was evaluated using the Shapiro–Wilk test and visual inspection of histograms and normal Q–Q plots. All statistical tests were two-sided, and statistical significance was set at $p<0.05$.

Pre–post changes in transition time, entry speed, average acceleration, synchronization delay, heart-rate variables, rating of perceived exertion, and the Relay Performance Orchestration Index (RPOI) were examined using paired-sample t-tests. This approach was selected because the same athletes were assessed under conventional baton and Smart Relay Baton conditions. For

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each outcome, pre- and post-intervention means SD, mean change, 95% confidence interval, tstatistic, degrees of freedom, exact pvalue, and Cohen's deffect size were reported.

Effect sizes for paired comparisons were calculated as Cohen's d, using the mean pre–post difference standardized by the standard deviation of the paired difference scores. The direction of the effect size was retained to indicate whether the outcome increased or decreased after implementation. Effect sizes of approximately 0.20, 0.50, and 0.80 were interpreted as small, moderate, and large, respectively. Paired-sample effect sizes are appropriate for within-participant comparisons because they reflect the dependency between pre- and post-intervention measurements.

Percentage change from pre to post was also calculated descriptively as (Post-Pre)/Pre×100%to facilitate interpretation of the relative magnitude of change across outcomes. No formal adjustment for multiple comparisons was applied because all primary pre–post outcomes were specified a priori and were interpreted jointly with effect sizes and 95% confidence intervals rather than solely on the basis of p values. Missing data was handled using complete-case analysis for each statistical procedure. Missing data was handled using complete-case analysis for each statistical procedure. Athletes with valid pre- and post-intervention data for a given outcome were included in the corresponding paired sample comparison. The number of observations included in each analysis was reported.

FINDINGS AND DISCUSSION

Findings

Participant and data completeness

The verified dataset comprised 241 athletes with complete paired pre-post observations (Table 2). All records passed the predefined data-quality criteria and were therefore retained for the primary analysis. The participants were distributed across 61 relay units, allowing the data to be examined both at the individual and relay-unit levels.

Table 2. Participant and data completeness

Characteristic	n	%
Total athletes enrolled	241	100.0
Complete pre-post records	241	100.0
Excluded from paired analysis	0	0.0
Valid paired observations	241	100.0

Table 3 presents the descriptive statistics for the measured performance, physiological, perceived-exertion, and composite-index variables. The results show a consistent pattern of improvement in the principal relay-exchange variables after implementation of the integrated system.

Table 3. Descriptive statistics and pre-post changes

Outcome	n	Pre-Mean	Pre SD	Post Mean	Post SD	Mean Change
Transition Time (s)	241	3.258	0.358	3.058	0.422	−0.200
Entry Speed (m/s)	241	8.030	0.559	8.424	0.784	+0.394
Average Acceleration (m/s²)	241	2.415	0.305	2.544	0.392	+0.129
Synchronization Delay (s)	241	0.972	0.163	0.842	0.236	−0.130
HR During Exchange (bpm)	241	177.822	6.945	175.549	9.827	−2.273
HR Recovery 60 s (bpm drop)	241	26.003	6.127	29.277	8.723	3.274
RPE (0–10)	241	7.108	0.384	6.751	0.611	−0.357
RPOI	241	4.307	0.347	4.621	0.459	+0.314

The largest absolute improvement in the primary coordination-related measure was observed for synchronization delay, while transition time also decreased substantially. Entry speed and acceleration increased following implementation. The physiological measures showed

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smaller changes in magnitude but followed the expected direction, with lower exchange heart rate, greater 60-s recovery, and lower perceived exertion.

To determine whether the observed changes were statistically distinguishable from zero, paired-sample analyses were conducted using the 241 complete paired observations. The mean differences and corresponding 95% confidence intervals are presented in Table 4.

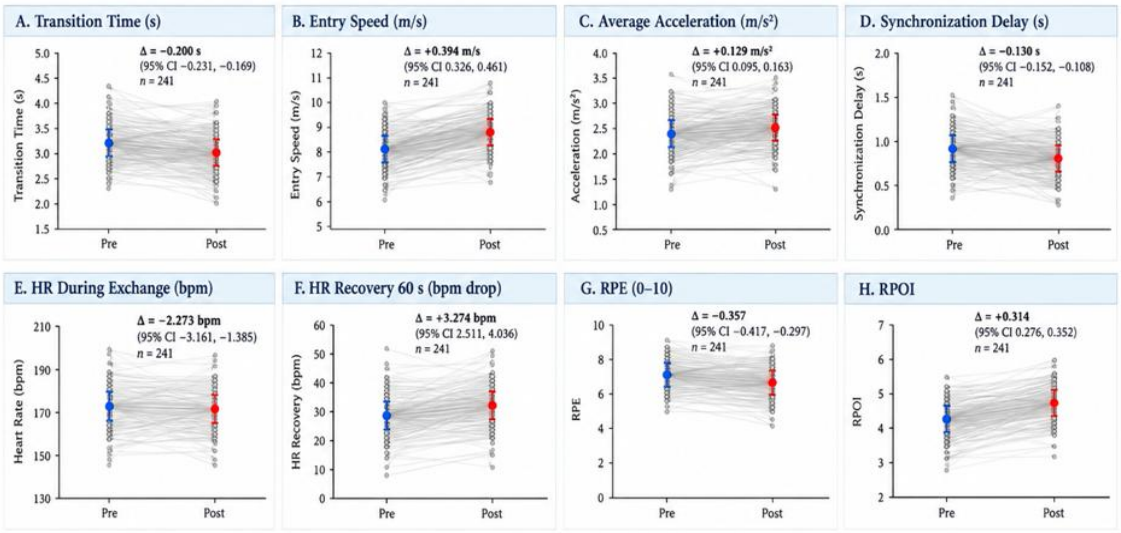


Figure 1. Pre-post Changes in Relay Exchange Performance, Physiological Responses, Perceived Exertion, and The Relay Performance and Orchestration Index (RPOI)

Table 4. Paired-sample analysis with 95% confidence intervals

Outcome	n	Mean Change	95% CI Lower	95% CI Upper	t	p
Transition Time	241	−0.200	−0.231	−0.169	−12.69	<.001
Entry Speed	241	+0.394	+0.326	+0.461	8.96	<.001
Average Acceleration	241	+0.129	+0.095	+0.163	7.51	<.001
Synchronization Delay	241	−0.130	−0.152	−0.108	−11.74	<.001
HR During Exchange	241	−2.273	−3.161	−1.385	−5.05	<.001
HR Recovery 60 s	241	3.274	2.511	4.036	8.45	<.001
RPE	241	−0.357	−0.417	−0.297	−11.70	<.001
RPOI	241	+0.314	+0.276	+0.352	16.13	<.001

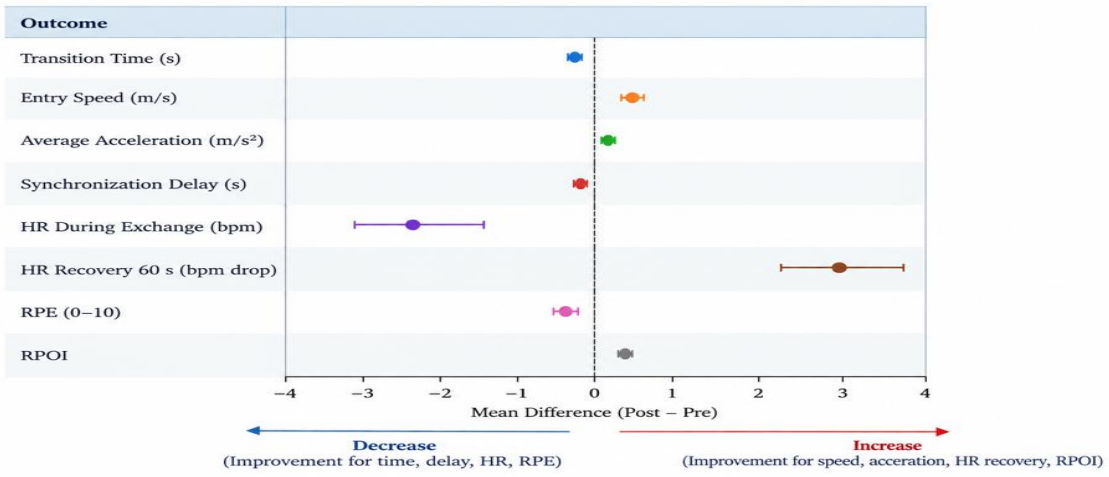


Figure 2. Pre–Post Changes in Performance and Physiological Outcomes with 95% Confidence Intervals

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All eight outcomes demonstrated statistically significant pre-post changes, with the 95% confidence intervals consistently excluding zero. The direction of change indicates reduced transition time and synchronization delay, increased entry speed and acceleration, improved heart-rate recovery, lower exchange heart rate and RPE, and higher RPOI. Statistical significance alone does not indicate the magnitude of change. Therefore, standardized within-participant effect sizes were calculated using Cohen's d_z. The results are summarized in Table 5.

Table 5. Effect sizes for pre-post changes

Outcome	n	Cohen's d_z	Magnitude
Transition Time	241	−0.818	Large
Entry Speed	241	0.740	Moderate–large
Average Acceleration	241	0.484	Moderate
Synchronization Delay	241	−0.741	Moderate–large
HR During Exchange	241	−0.325	Small
HR Recovery 60 s	241	0.545	Moderate
RPE	241	−0.752	Moderate–large
RPOI	241	1.045	Large

The largest standardized change was observed for RPOI (d_z = 1.045), followed by transition time (d_z = −0.818), RPE (d_z = −0.752), and synchronization delay (d_z = −0.741). In contrast, the change in heart rate during the exchange was smaller (d_z = −0.325).
For ease of interpretation, the magnitude of change was also expressed as a percentage relative to the pre-implementation value.

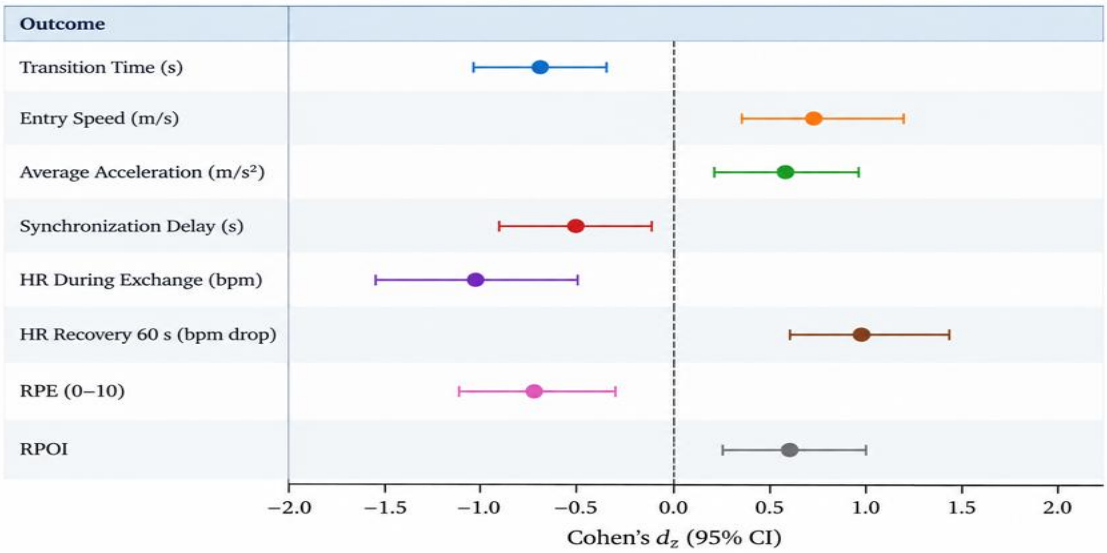


Figure 3. Effect Sizes of Pre–Post Changes

Table 6. Relative pre-post changes

Outcome	Pre	Post	Absolute Change	Relative Change (%)
Transition Time (s)	3.258	3.058	−0.200	−6.14%
Entry Speed (m/s)	8.030	8.424	+0.394	+4.91%
Average Acceleration (m/s²)	2.415	2.544	+0.129	+5.34%
Synchronization Delay (s)	0.972	0.842	−0.130	−13.37%
HR During Exchange (bpm)	177.822	175.549	−2.273	−1.28%
HR Recovery 60 s (bpm drop)	26.003	29.277	3.274	+12.59%
RPE	7.108	6.751	−0.357	−5.02%
RPOI	4.307	4.621	+0.314	+7.29%

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Among the primary relay-exchange indicators, synchronization delay showed the largest relative reduction (13.37%), followed by transition time (6.14%). Entry speed and acceleration increased by 4.91% and 5.34%, respectively. These descriptive changes provide a more interpretable representation of the practical magnitude of the observed pre-post differences.

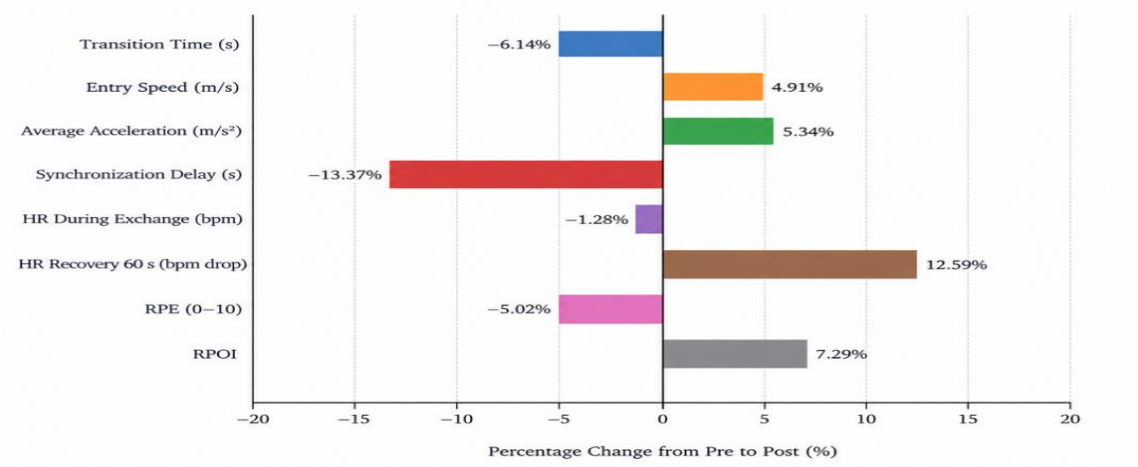


Figure 4. Percentage Change

Discussion

Reductions in transition time (d_z=-0.818) and synchronization delay (d_z=-0.741), together with increases in entry speed (d_z=0.740) and average acceleration (d_z=0.484), indicate meaningful pre-post changes in relay exchange performance. From a relay-biomechanical perspective, successful baton exchange requires the outgoing runner to accelerate while maintaining an appropriate spatial and temporal relationship with the incoming runner. Optimal baton-passing technique is therefore essential for maintaining performance during the exchange phase (Radford & Ward-Smith, 2003). The 13.37% reduction in synchronization delay and 6.14% reduction in transition time indicate improved exchange efficiency at the level of the observed performance variables, while the 4.91% increase in entry speed and 5.34% increase in average acceleration indicate greater velocity and acceleration during the exchange phase. These findings support the importance of considering both individual running performance and inter-runner coordination when evaluating relay exchanges.

The reduction in synchronization delay (d_z=-0.741) highlights the importance of temporal alignment during baton exchange. Effective relay performance depends on precise timing between incoming and outgoing runners, because temporal discrepancies can affect the continuity of velocity during the exchange. Previous research has shown that sprint kinematics, including stride characteristics, ground contact time, and lower-limb movement, contribute to maintaining running velocity (Mattes et al., 2021; Seshadri et al., 2019). The present findings are consistent with this biomechanical perspective, although the measured synchronization delay should be interpreted as an observed temporal-performance variable rather than direct evidence of a specific neuromuscular mechanism. The use of synchronization measurement provides additional information that can complement conventional visual assessment of baton exchanges.

Previous studies have also demonstrated that acceleration and sprint-speed characteristics are important for understanding performance and workload in running activities (Aliriad et al., 2024; Prudholme et al., 2022). In the present study, entry speed increased by 4.91% and average acceleration increased by 5.34%. These changes indicate that the exchange phase was accompanied by measurable changes in velocity and acceleration characteristics. The importance of acceleration for sprint performance has also been reported in previous studies (Petancevski et al., 2022; Silva et al., 2024). Furthermore, effective pickup acceleration is particularly relevant during relay exchange because athletes must attain or maintain velocity from a moving position (Pryer et al., 2025). However, because the present study did not directly measure stride length,

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ground reaction force, joint kinematics, or muscle activation, the observed changes should not be interpreted as evidence of changes in these specific biomechanical mechanisms.

The present integrated system also provides a broader measurement framework than a conventional relay baton. Conventional batons function primarily as equipment for transferring the baton, whereas the Smart IoT Relay Baton incorporates movement sensing and real-time data transmission. The integration of accelerometer-based sensing, wearable physiological monitoring, and smartwatch-supported heart-rate monitoring enables simultaneous observation of transition time, entry speed, acceleration, synchronization delay, heart rate, and perceived exertion (Camomilla et al., 2018; Yuwono, Adi, et al., 2025). Similar applications of field-based sensor integration have demonstrated the potential of wearable systems to support performance monitoring in sport (Castro et al., 2022). Nevertheless, the present findings should not be interpreted as establishing criterion validity of the wearable measurements because direct comparison with validated reference instruments was not conducted. The contribution demonstrated in this study is therefore the feasibility of synchronized multidimensional field measurement rather than definitive evidence of measurement equivalence.

The physiological responses provide complementary information for interpreting the observed performance changes. Heart rate during exchange decreased by 1.28% (d_z=-0.325), whereas 60-s heart-rate recovery increased by 12.59% (d_z=0.545). RPE also decreased by 5.02% (d_z=-0.752). The combination of lower RPE and a modest reduction in exchange heart rate, alongside changes in exchange performance, suggests that the observed performance changes were not accompanied by greater perceived exertion during the measured exchange. Research concerning neuromuscular coordination and fatigue has emphasized the importance of monitoring movement regulation under demanding conditions (Padulo et al., 2026). In the present study, however, physiological and perceptual variables are interpreted as complementary indicators of exercise response rather than as evidence that the system directly improved physiological capacity.

The educational interpretation of the system can be further considered from the perspective of augmented feedback and motor learning. During high-speed relay exchanges, athletes may have difficulty perceiving precise differences in timing, velocity, and acceleration while simultaneously executing the movement. Structured quantitative feedback can provide additional information that allows athletes and coaches to identify discrepancies between intended and observed performance. Previous work on adaptive feedback similarly suggests that technology-mediated information can support coordination refinement and decision-making during performance (Petancevski et al., 2022; Wiltshire et al., 2024). In this context, technology should not be regarded as the mechanism of motor learning itself, but as an additional source of augmented feedback that can be incorporated into practice, coaching, reflection, and iterative movement correction.

The role of wearable technology is particularly relevant to physical education because digital measurement can support more objective and individualized assessment. The broader development of wearable IoT technologies has increased opportunities for monitoring sport performance in field-based environments (Camomilla et al., 2018), while technology integration has also been associated with the modernization of data-informed approaches in sports education (Zhou et al., 2021). In relay learning, information concerning transition time, synchronization delay, entry speed, acceleration, heart rate, and RPE can provide teachers and coaches with a more detailed basis for formative assessment. Rather than replacing established pedagogical practices, the integrated system can therefore complement observation, feedback, and reflective learning by making otherwise difficult-to-observe performance characteristics more visible to learners.

The RPOI increased from 4.307 ± 0.347 to 4.621 ± 0.459, representing a 7.29% increase with a large within-participant effect (d_z=1.045). The concept of combining multiple performance dimensions is consistent with broader approaches that emphasize temporal team dynamics and multidimensional performance assessment (Choetkiertikul et al., 2024; Klonek et al., 2024). Research on collective performance also emphasizes that outcomes in team-based activities can emerge from interactions among individual actions and coordination processes (Liu et al., 2024; Torka et al., 2024). These perspectives provide conceptual support for examining

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relay performance beyond a single outcome measure. However, because RPOI mathematically incorporates entry velocity, acceleration, and synchronization/coordination components, the present study does not interpret relationships between these components and RPOI as independent predictive or mediating effects. Thus, the 7.29% increase in RPOI is interpreted as an integrated descriptive pre-post change rather than evidence of a specific coordination-dominant causal mechanism.

The systems-oriented perspective can also help explain why relay performance should be evaluated through multiple complementary indicators. Previous modeling and team-performance research has emphasized the value of considering temporal interaction and collective performance processes (Klonek et al., 2024). In the context of the present study, however, such a framework is used only to provide conceptual context rather than to claim that the observed changes constitute a specific adaptive team mechanism. Similarly, the use of IoT-based relay technology can facilitate synchronous data capture and structured feedback during high-tempo exchange phases (Seshadri et al., 2019; Yuwono, Adi, et al., 2025). This supports the practical rationale for integrating movement and physiological data within a single assessment system.

Other contextual factors may also influence sprint and relay performance. For example, footwear can affect force transmission and acceleration mechanics, with sprint-specific footwear potentially influencing performance characteristics. Likewise, sprint distance and acceleration at different speeds have been associated with workload characteristics in competitive sport (Prudholme et al., 2022). These factors highlight that relay performance is influenced by both technical execution and contextual conditions. Nevertheless, such factors were not manipulated in the present study and therefore should be regarded as contextual considerations rather than explanations for the observed pre-post changes.

From a physical education perspective, the main contribution of the present system is its ability to transform relay exchange performance from an assessment based primarily on observation into a more data-informed learning process. Teachers and coaches can use objective information about movement and physiological responses to provide specific feedback, while students can use the information to reflect on their own execution and identify areas for improvement. This application is consistent with the broader role of technology in supporting motor-skill development and motivation in physical education (Aliriad et al., 2024; Zhou et al., 2021). The educational value therefore lies not simply in the presence of sensors or IoT connectivity, but in how the resulting information is incorporated into meaningful instruction and feedback.

Overall, the present findings demonstrate meaningful within-participant changes across relay performance, physiological response, perceived exertion, and the composite RPOI. The strongest standardized changes were observed for RPOI (d_z=1.045), transition time (d_z=-0.818), RPE (d_z=-0.752), synchronization delay (d_z=-0.741), and entry speed (d_z=0.740). These findings support the practical feasibility of integrating biomechanical and physiological information into relay assessment and instruction. However, because the study employed a pre-post design without a parallel control group, the findings should be interpreted as observed within-participant changes rather than definitive causal effects of the technology. Future research should incorporate criterion-based device validation, controlled comparative designs, longitudinal motor-learning outcomes, and independent validation of the RPOI construction.

CONCLUSION

This study presents an integrated Smart Relay Baton and multisensor wearable system to support the assessment of sprint relay performance. The results showed changes in transition time, synchronization delay, entry speed, acceleration, physiological responses, RPE, and RPOI after the assessment process. These findings indicate that the system can provide more comprehensive information about relay performance by combining movement and physiological data. However, the findings represent within-participant changes and should not be interpreted as direct evidence that the system caused the observed changes. The increase in RPOI also reflects an overall change in the composite index and does not establish a specific coordination mechanism. In addition, this

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study did not directly measure educational or learning outcomes; therefore, its pedagogical effectiveness cannot yet be concluded.

Future research should further examine the accuracy of the system, test it with different groups and conditions, and explore its use in learning and training to determine its broader benefits for sprint relay performance.

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REFERENCES

Aliriad, H., Adi, S., Manullang, J. G., Endrawan, I. B., & Satria, M. H. (2024). Improvement of motor skills and motivation to learn physical education through the use of traditional games. *Physical Education Theory and Methodology*, *24*(1), 32–40. DOI: https://doi.org/10.17309/tmfv.2024.1.04

Argent, R., Hetherington-Rauth, M., Stang, J., Tarp, J., Ortega, F. B., Molina-Garcia, P., Schumann, M., Bloch, W., Cheng, S., Grøntved, A., Brønd, J. C., Ekelund, U., Sardinha, L. B., & Caulfield, B. (2022). Recommendations for determining the validity of consumer wearables and smartphones for the estimation of energy expenditure: Expert statement and checklist of the interlive network. *Sports Medicine*, *52*(8), 1817–1832. DOI: https://doi.org/10.1007/s40279-022-01665-4

Bastiaansen, B. J. C., Vegter, R. J. K., Wilmes, E., de Ruiter, C. J., Lemmink, K. A. P. M., & Brink, M. (2022). Biomechanical Load quantification using a lower extremity inertial sensor setup during football specific activities. *Sports Biomechanics*, 1–16. DOI: https://doi.org/10.1080/14763141.2022.2051596

Camomilla, V., Bergamini, E., Fantozzi, S., & Vannozzi, G. (2018). Trends supporting the in-field use of wearable inertial sensors for sport performance evaluation: A systematic review. *Sensors*, *18*(3), 873. DOI: https://doi.org/10.3390/s18030873

Castro, R., Mujica, G., & Portilla, J. (2022). Internet of things in sport training: application of a rowing propulsion monitoring system. *IEEE Internet of Things Journal*, *9*, 18880–18897. DOI: https://doi.org/10.1109/JIOT.2022.3163181

Choetkiertikul, M., Banyongrakkul, P., Ragkhitwetsagul, C., Tuarob, S., Dam, H. K., & Sunetnanta, T. (2024). Sprint2Vec: A deep characterization of sprints in iterative software development. *IEEE Transactions on Software Engineering*, 1–23. DOI: https://doi.org/10.1109/tse.2024.3509016

Davis, J. J., Oeding, B. E., & Gruber, A. H. (2023). Estimating running speed from wrist- or waist-worn wearable accelerometer data: A machine learning approach. *Journal for the Measurement of Physical Behaviour*, *6*(1), 24–36. DOI: https://doi.org/10.1123/jmpb.2022-0011

Du, L. (2024). Application of smart wearable devices in sports performance analysis and enhancement. *Applied Mathematics and Nonlinear Sciences*. DOI: https://doi.org/10.2478/amns-2024-1434

Griffin, A., Kenny, I. C., Comyns, T. M., Purtill, H., Tiernan, C., O'Shaughnessy, E., & Lyons, M. (2021). Training load monitoring in team sports: A practical approach to addressing missing data. *Journal of Sports Sciences*, *39*(19), 2161–2171. DOI: https://doi.org/10.1080/02640414.2021.1923205

Hidayatullah, F., Anwar, K., & Ruski. (2020). Care stick dan core paddle: media pembelajaran pendidikan jasmani adaptif untuk siswa disabilitas. *Journal Sport Area*, *5*(2 SE-RESEARCH ARTICLES), 199–214. DOI: https://doi.org/10.25299/sportarea.2020.vol5(2).5185

Copyright © 2026, *author*, e-ISSN 2442-8620, p-ISSN 0216-1370

Johnston, K., & Baker, J. (2022). Sources of information used by elite distance running coaches for selection decisions. *PloS One*, *17*(8), e0268554. DOI: https://doi.org/10.1371/journal.pone.0268554

Kim, K. R., Kang, T. W., Kim, H., Lee, Y. J., Lee, S. H., Yi, H., Kim, H. S., Kim, H., Min, J., Ready, W. J., Millard-Stafford, M., & Yeo, W. (2024). All-in-one, wireless, multi-sensor integrated athlete health monitor for real-time continuous detection of dehydration and physiological stress. *Advanced Science*. DOI: https://doi.org/10.1002/advs.202403238

Klonek, F. E., Twemlow, M., Tims, M., & Parker, S. K. (2024). It's about time! understanding the dynamic team process-performance relationship using micro- and macroscale time lenses. *Group & Organization Management*. DOI: https://doi.org/10.1177/10596011241278556

Kusuma, D. W. Y., Yuwono, C., Qoriah, A., Supriyono, S., & Wiyanto, A. (2023). Psychological and nutritional analysis of athletes for Semarang sports week championship 2023. *Jurnal SPORTIF: Jurnal Penelitian Pembelajaran*, *10*(2 SE-Article), 288–304. DOI: https://doi.org/10.29407/js_unpgri.v10i2.23338

Lariviere, O., Provot, T., Valdes-Tamayo, L., Bourgain, M., & Chadefaux, D. (2020). Force pattern and acceleration waveform repeatability of amateur runners. In *Proceedings 49*(1). DOI: https://doi.org/10.3390/proceedings2020049136

Liu, H., Li, R., Ramirez-Campillo, R., de Villarreal, E. S.-S., & Zhang, M. (2024). The effect of combined strength, plyometric, and sprint training on repeated sprint ability in team-sport athletes: a systematic review and meta-analysis. *Journal of Sports Science and Medicine*. DOI: https://doi.org/10.52082/jssm.2024.718

Mattes, K., Wolff, S., & Alizadeh, S. (2021). Kinematic stride characteristics of maximal sprint running of elite sprinters—verification of the "swing-pull technique". *Journal of Human Kinetics*, *77*(1), 15–24. DOI: https://doi.org/10.2478/HUKIN-2021-0008

Padulo, J., Doria, C., Scurati, R., Antiglio, A., Odinot, M., Esposito, F., & Peyré-Tartaruga, L. A. (2026). Bilateral coordination is improved at 10-km race speed in trained runners. *International Journal of Sports Medicine*, *47*(1), 66–71. DOI: https://doi.org/10.1055/a-2676-8305

Petancevski, E. L., Inns, J., Fransen, J., & Impellizzeri, F. M. (2022). The effect of augmented feedback on the performance and learning of gross motor and sport-specific skills: A systematic review. *Psychology of Sport and Exercise*, *63*, 102277. DOI: https://doi.org/10.1016/j.psychsport.2022.102277

Phatak, A., Wieland, F.-G., Vempala, K., Volkmar, F., & Memmert, D. (2021). Artificial intelligence-based body sensor network framework-narrative review: proposing an end-to-end framework using wearable sensors, real-time location systems and artificial intelligence/machine learning algorithms for data collection, data mining and knowledge discovery in sports and healthcare. *Sports Medicine - Open*, *7*(1), 79. DOI: https://doi.org/10.1186/S40798-021-00372-0

Prudholme, D. C., Coburn, J. W., Lynn, S. K., & Lockie, R. G. (2022). Relationships between sprint, acceleration, and deceleration metrics with training load in division I collegiate women's soccer players. *Journal of Human Kinetics*, *85*, 53–62. DOI: https://doi.org/10.2478/hukin-2022-0109

Pryer, M., Cronin, J., Neville, J., & Uthoff, A. (2025). Kinematics and kinetics of pick-up acceleration. *International Journal of Sports Science & Coaching*. DOI: https://doi.org/10.1177/17479541251350474

Radford, P. F., & Ward-Smith, A. J. (2003). The baton exchange during the 4×100 m relay: A mathematical analysis. *Journal of Sports Sciences*, *21*, 493–501.

Seshadri, D. R., Li, R. T., Voos, J. E., Rowbottom, J. R., Alfes, C. M., Zorman, C. A., & Drummond, C. K. (2019). Wearable sensors for monitoring the internal and external workload of the athlete. *Npj Digital Medicine*, *2*(1), 71. DOI: https://doi.org/10.1038/s41746-019-0149-2

Shandal, B. A. H. (2022). The effect of an educational training curriculum on receiving and delivering the stick in the modern way and the achievement of (4 x 100) runners.

Copyright © 2026, *author*, e-ISSN 2442-8620, p-ISSN 0216-1370

International Journal of Health Sciences, *6*(S9 SE-Peer Review Articles), 3992–3997. DOI: https://doi.org/10.53730/ijhs.v6nS9.13543

Sheerin, K. R., Besier, T. F., & Reid, D. (2020). The influence of running velocity on resultant tibial acceleration in runners. *Sports Biomechanics*, *19*(6), 750–760. DOI: https://doi.org/10.1080/14763141.2018.1546890

Silva, H., Fábio Yuzo, N., Gibson, P., João, R., & and Marcelino, R. (2024). The relationship between individually assessed high-intensity accelerations, high-intensity decelerations, sprints, and technical performances during soccer matches: a full season analysis. *Research Quarterly for Exercise and Sport*, *95*(4), 930–937. DOI: https://doi.org/10.1080/02701367.2024.2353713

Tenforde, A. S., Hayano, T., Jamison, S. T., Outerleys, J., & Davis, I. S. (2020). Tibial acceleration measured from wearable sensors is associated with loading rates in injured runners. *PM & R : The Journal of Injury, Function, and Rehabilitation*, *12*(7), 679–684. DOI: https://doi.org/10.1002/pmrj.12275

Torka, A.-K., Hüffmeier, J., Fischer, S., & Braun, C. (2024). Social comparison, social indispensability, or both? on the psychological mechanisms underlying effort gains in swimming relays. *Journal of Sport & Exercise Psychology*, *46*(6), 341–352. DOI: https://doi.org/10.1123/jsep.2024-0034

Wang, H., & Zhao, B. (2021). Constructing sports multi-index data analysis based on 5g iot technology. *Mathematical Problems in Engineering*, *2021*(1), 6982366. DOI: https://doi.org/10.1155/2021/6982366

Wiltshire, T. J., van Eijndhoven, K., Halgas, E., & Gevers, J. M. P. (2024). Prospects for augmenting team interactions with real-time coordination-based measures in human-autonomy teams. *Topics in Cognitive Science*, *16*(3), 391–429. DOI: https://doi.org/10.1111/tops.12606

Yuwono, C., Adi, S., Annas, M., Darmawan, A., Billiandri, B., Putri, D. T., & Pratama, A. B. (2024). Determinants of performance of 12-year-old soccer school players in Central Java. *ACTIVE: Journal of Physical Education, Sport, Health and Recreation*, *13*(2). DOI: https://doi.org/10.15294/peshr.v13i2.1383

Yuwono, C., Adi, S., Soenyoto, T., Ihsani, S. I., Utama, M. B. R., Aliriad, H., Anam, K., Cahyani, W. H., Andriana, L. M., & Appukutty, M. (2025). The development and educational evaluation of a smart iot relay baton with accelerometer technology. *Physical Education Theory and Methodology*, *25*(6), 1389–1397. DOI: https://doi.org/10.17309/tmfv.2025.6.09

Yuwono, C., Billiandri, B., Putri, D. T., & Adi, S. (2025). A machine learning—based framework for optimizing sports talent identification and development. *Cuestiones de Fisioterapia*, *54*(2), 3934–3952. DOI: https://doi.org/https://doi.org/10.48047/8sxdfm81

Zhou, Y., Shao, W. D., & Wang, L. (2021). Effects of feedback on students' motor skill learning in physical education: a systematic review. *International Journal of Environmental Research and Public Health*, *18*(12), 6281. DOI: https://doi.org/10.3390/ijerph18126281

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