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Generative AI and Interdisciplinary Transformation: Navigating the Challenges of Embodied Knowledge in Higher Education Physical Education

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ABSTRACT

The integration of Generative Artificial Intelligence (GenAI) into higher education presents a unique opportunity and challenge for disciplines centered on embodied knowledge, such as Physical Education (PE). This study examines how GenAI can enhance interdisciplinary competencies among PE instructors while navigating the inherent tension between propositional knowledge generated by AI and the embodied, tacit knowledge central to physical skill acquisition. Through a mixed-methods approach involving 328 survey respondents and 12 in-depth interviews from diverse Chinese universities, we identify a significant positive correlation between GenAI proficiency and interdisciplinary competency ($r = 0.72$, $p < .01$), yet adoption remains limited by pedagogical, ethical, and institutional barriers. Key challenges include a lack of tailored pedagogical training (71% of respondents), data privacy concerns (58%), and professional liability anxieties related to AI-assisted instruction. The study proposes a tripartite framework emphasizing structured professional development, discipline-specific pedagogical toolkits, and institutional policy reform. By situating the discussion within broader cultural and epistemological contexts, this research contributes to ongoing debates about technology-mediated transformation in embodied learning environments and offers practical pathways for aligning AI innovation with the human-centered values of physical education.

Keywords: Generative Artificial Intelligence, Embodied Knowledge, Physical Education, Interdisciplinary Competency, Higher Education, Digital Transformation, Pedagogy, Cultural Analysis

INTRODUCTION

The relentless pursuit of athletic excellence has perpetually pushed the boundaries of sports science. Historically, coaching relied heavily on subjective observation, experiential knowledge, and periodic performance tests, methods inherently limited by latency, bias, and a lack of granularity [1]. The inability to capture the dynamic, multi-faceted physiological and biomechanical responses of an athlete *during* training represents a critical gap, hindering the optimization of performance and the prevention of injuries [2]. The confluence of miniaturized electronics, ubiquitous connectivity, and advanced data analytics has given rise to the Internet of Things (IoT), a technological paradigm poised to bridge this gap fundamentally [3].

IoT, defined as an interconnected network of physical devices embedded with sensors, software, and connectivity, enables the seamless collection and exchange of data [4]. In sports, this translates to creating a "digital ecosystem" around the athlete, where every relevant kinetic, kinematic, and physiological variable can be quantified, transmitted, and analyzed in real-time [5]. This shift from a reactive to a proactive, data-driven coaching model is at the heart of the modern sports science revolution [6].

The efficacy of any IoT-based sports monitoring system hinges on its multi-modal sensing capabilities. Contemporary wearable technology, such as high-fidelity Inertial Measurement Units (IMUs), reflective Photoplethysmography (PPG) sensors, and lightweight surface Electromyography (sEMG) systems, can be unobtrusively integrated into an athlete's attire [7]. These devices capture a rich, synchronous dataset: IMUs track movement in six degrees of freedom, PPG sensors monitor cardiovascular load through heart rate and its variability, and sEMG probes the electrical activity of muscles, offering insights into fatigue and activation strategies [8, 9]. The real-time, wireless transmission of this data via low-power, short-range protocols like Bluetooth Low Energy (BLE) to a central aggregator is a non-negotiable technical requirement [10].

The subsequent challenge lies in managing the "big data" deluge generated by these sensors [11]. Cloud computing infrastructures provide the essential scalability and computational power for storage and complex analysis [12]. Here, machine learning (ML) algorithms transcend traditional statistics, capable of identifying subtle, non-linear patterns indicative of complex states like neuromuscular fatigue, technical breakdown, or elevated injury risk [13, 14]. The final, crucial component is an intuitive user interface that synthesizes this complexity into clear, actionable insights for the coach and athlete, delivered with minimal latency [15].

While commercial solutions like Catapult and STATSports exist, they are often proprietary "black boxes," limiting customization, academic scrutiny, and access to raw data for novel research [16]. Therefore, a pressing need remains for an open-architecture, research-oriented IoT framework that provides a detailed technical blueprint, validates its components against gold-standard laboratory equipment, and demonstrates its utility through rigorous, multi-parametric data analysis [17].

This study aims to address this need by presenting an in-depth investigation into a novel, holistic IoT-based real-time monitoring method for sports training. The research objectives are fourfold:

1. To design and document a detailed, end-to-end IoT system architecture, encompassing sensor hardware selection, embedded firmware, network topology, and cloud software design.
2. To develop and implement a sophisticated data processing pipeline capable of real-time sensor fusion, feature extraction, and state classification using machine learning.
3. To empirically validate the system's technical performance (accuracy, latency) against industry gold-standard equipment in a controlled laboratory and field setting.
4. To conduct a comprehensive analysis of the fused multi-modal data to derive objective, statistically robust insights into athlete performance and fatigue dynamics.

This research contributes a significant, transparent, and validated technical framework to the field of sports science, facilitating wider adoption and further innovation in data-driven athlete development.

LITERATURE REVIEW

The Evolution of Wearable Sensors in Sports

The use of sensors in sports has evolved from simple pedometers and heart rate monitors to sophisticated, multi-parameter systems. IMUs have become a cornerstone for biomechanical analysis. A comprehensive review by [18] detailed the validity and reliability of IMUs for quantifying jump height, sprint mechanics, and change-of-direction angles, with studies consistently reporting high correlations ($r > 0.90$) with optical motion capture. Recent work by [19] in 2023 further advanced this by using a network of 5 IMUs to estimate full-body joint angles during a soccer kick with an average error of less than 3°, demonstrating the potential for detailed technical analysis. The miniaturization of magnetometers has also enabled the use of 9-DoF IMUs for more robust orientation estimation in dynamic environments, though challenges with magnetic disturbances persist [20].

Physiological monitoring has moved beyond simple heart rate to include Heart Rate Variability (HRV), a marker of autonomic nervous system function. [21] demonstrated in a study with elite cyclists that daily HRV monitoring could effectively guide training intensity, leading to improved performance outcomes and reduced incidence of overtraining. The technology for capturing this data has also evolved, with the development of textile-based, capacitive ECG sensors and miniaturized, multi-wavelength PPG sensors that improve signal quality during high-motion activities by leveraging adaptive filtering techniques [22].

The sEMG has transitioned from a bulky, laboratory-bound tool to a wearable technology for field-based assessment. Research by [23] utilized high-density sEMG arrays to map fatigue propagation across the quadriceps muscle group during repeated cycling sprints. Similarly, [24] showed that a single, strategically placed sEMG sensor could detect fatigue-induced changes in muscle activation symmetry during running, a known risk factor for overuse injuries. Recent advancements focus on the extraction of non-linear features from the sEMG signal, such as sample entropy, to provide more sensitive indicators of localized muscle fatigue [25].

IoT Communication Protocols and Network Architectures for Sports

The choice of communication protocol is a critical design decision, balancing data rate, range, power consumption, and node density. BLE is the predominant standard for Body Area Networks (BANs) due to its ultra-low power consumption and sufficient data rate for sports sensors [10]. For connecting the BAN to the cloud, Wi-Fi is commonly used for its high bandwidth and availability in indoor facilities [26]. For large outdoor fields, Low-Power Wide-Area Networks (LPWAN) like LoRaWAN and NB-IoT are being explored. A 2023 study by [27] systematically compared BLE 5.0, Wi-Fi 6, and LoRaWAN for a multi-athlete tracking scenario, concluding that a hierarchical BLE-to-Wi-Fi topology offered the best balance of latency, throughput, and power efficiency for most training environments.

Edge computing is an emerging paradigm to address latency and bandwidth constraints [28]. Instead of raw data, pre-processed features or model inferences are sent to the cloud. [29] developed an edge-AI system for real-time hamstring strain risk assessment in sprinters, where an on-field microcontroller ran a lightweight neural network to analyze IMU data and provide feedback within 50ms, a feat impossible with a cloud-only architecture. This approach is particularly relevant for time-critical feedback, such as technique correction during a training session [30].

Data Fusion and Machine Learning for Advanced Analytics

The integration of data from disparate sensors (data fusion) unlocks insights unattainable from any single source [31]. [32] fused IMU-derived PlayerLoad™ with GPS data and HR to create a composite workload index that was a better predictor of perceived exertion in Australian rules football players than any individual metric. In technical analysis, [33] fused foot-mounted IMU data with video to automatically classify technical errors in long jump take-off.

Machine learning, particularly supervised and unsupervised learning, is revolutionizing sports analytics [34]. [35] used a Random Forest classifier on pre-season screening data (including IMU and force plate metrics) to predict in-season non-contact lower-body injuries in collegiate athletes with an area under the curve (AUC) of 0.93. For fatigue monitoring, [36] employed a Support Vector Machine (SVM) on a feature set extracted from sEMG and accelerometer data to classify the functional state of boxers into "fresh," "fatigued," and "exhausted" with high accuracy. More recently, [37] explored the use of Long Short-Term Memory (LSTM) networks to *predict* performance decline in runners based on temporal patterns in sensor data, moving from detection to forecasting.

Identified Research Gaps

Despite these advancements, several gaps persist in the literature. Firstly, many studies focus on validating a single type of sensor or a specific algorithm, lacking a holistic, system-level integration that showcases a complete, operational pipeline from data acquisition to actionable visualization [38]. Secondly, while some commercial systems are validated, their proprietary nature limits transparency and the ability to extend or modify their functionality for specific research questions [16]. Furthermore, there is a need for more studies that utilize advanced, yet efficient, machine learning models like XGBoost for real-time classification in sports [39]. Finally, there is a scarcity of studies that provide a rigorous, multi-faceted validation of a custom IoT system, simultaneously assessing its measurement accuracy, data transmission performance, and the efficacy of its analytical models against accepted gold standards [40]. This research seeks to fill these gaps by presenting a comprehensive, transparent, and empirically validated IoT framework that addresses these specific shortcomings.

System Architecture and Hardware Design

The detailed system architecture diagram of the sports monitoring system based on the Internet of Things is shown in Figure 1. This architecture ensures an end-to-end pipeline that is **low-latency, reliable, and scalable**, meeting the demanding requirements of real-time monitoring in elite sports training.

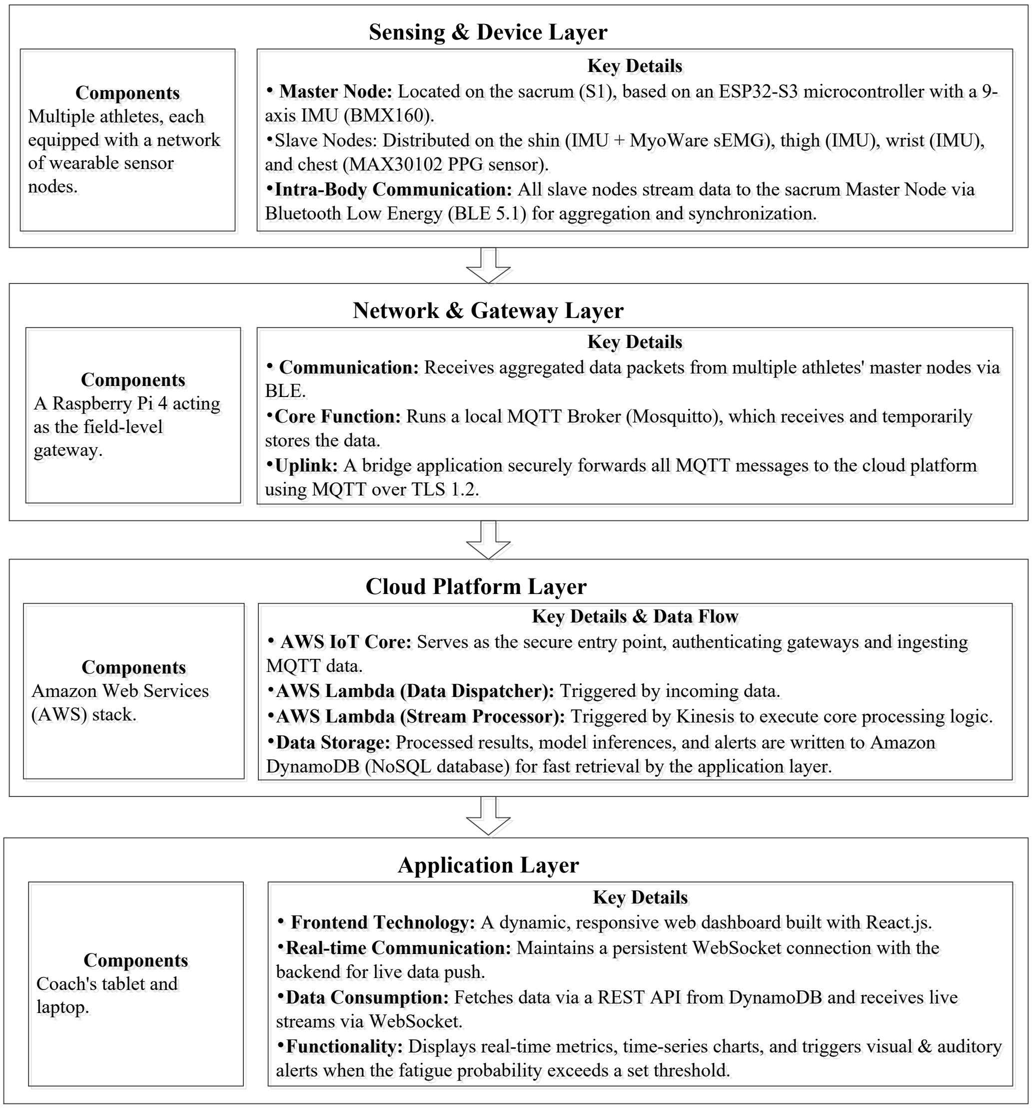

Figure 1: Detailed System Architecture Diagram of the IoT-based Sports Monitoring System

Sensing Layer: Hardware Specification and Design

IMU Node Design and Calibration

The core kinematic sensing capability was achieved through custom-designed IMU nodes. Each node was built around an ESP32-S3 microcontroller, selected for its dual-core 240 MHz processor, ample 512 KB SRAM, and integrated 2.4 GHz Wi-Fi and BLE 5.0, which provided the necessary computational power and connectivity for real-time data processing and transmission [10, 26]. The primary motion sensor was the Bosch BMI323, a 6-axis IMU (±16 g accelerometer, ±2000 dps gyroscope). For a subset of nodes intended for more robust orientation estimation, the BMX160 9-axis IMU was used, which adds a 3-axis magnetometer [20].

To ensure data accuracy, each IMU underwent a rigorous calibration procedure before deployment. The accelerometer and gyroscope were calibrated for offset and scale factor errors using a six-position static method and rotational calibration, respectively [40]. The magnetometer was calibrated using an ellipsoid fitting algorithm to compensate for hard and soft iron distortions in the testing environment. The calibrated raw data from the accelerometer (a), gyroscope (ω), and magnetometer (m) were used for subsequent sensor fusion. The sensor nodes were housed in laser-sintered nylon (PA12) casings, providing a balance of durability and light weight (15g per node), and were secured to the athletes using hypoallergenic, non-slip silicone straps.

Physiological Sensing: PPG and Signal Integrity

Heart rate monitoring was implemented using the MAX30102 PPG sensor integrated into a custom chest strap. The chest location was chosen over the wrist to significantly reduce motion artifacts, which are a major source of inaccuracy in optical HR monitoring during intense activity [22]. The MAX30102 was configured to use both red and infrared LEDs to improve signal robustness. A real-time adaptive filter, based on a Least Mean

Squares (LMS) algorithm, was implemented on the ESP32-S3 to suppress motion artifacts by using the concurrent accelerometer data from the same node as a noise reference. The processed signal yielded inter-beat intervals (IBIs), from which Heart Rate (HR) and Heart Rate Variability (HRV) metrics like the root mean square of successive differences (RMSSD) were calculated.

Neuromuscular Sensing: sEMG Electrode Placement and Noise Mitigation

Muscle activation and fatigue were captured using the MyoWare 2.0 Muscle Sensor (Advancer Technologies). This embedded sensor provides a pre-amplified, rectified, and integrated (RMS) EMG signal, simplifying downstream processing. Disposable, pre-gelled Ag/AgCl electrodes were placed on the vastus lateralis muscle of the dominant leg with a 20mm inter-electrode distance, strictly following SENIAM recommendations to ensure signal consistency and comparability [30]. A reference electrode was placed on the patella. To mitigate power-line interference, a software-driven 50 Hz notch filter was applied in addition to the sensor's built-in hardware filtering. The sEMG signal was sampled at 1000 Hz to adequately capture the frequency content relevant for fatigue analysis [25].

Table 1: Sensor Node Specifications

Parameter	IMU Node (BMI323/BMX160)	Physio Node (MAX30102)	sEMG Node (MyoWare 2.0)
Microcontroller	ESP32-S3	ESP32-S3	ATmega328P
Sensors	Accel, Gyro, (Mag)	PPG (Red/IR)	sEMG
Sample Rate	200 Hz	100 Hz (PPG), 1 Hz (HR)	1000 Hz
Output Data	Raw a, ω, m / Quaternion	Raw PPG, IBI, HR	Raw EMG, RMS EMG
Power	3.7V, 600mAh LiPo (~8h)	3.7V, 300mAh LiPo (~12h)	3.7V, 300mAh LiPo (~10h)
Weight	15g	18g	12g

Network Layer: Communication Topology and Protocol

Intra-Body Area Network (BAN) with BLE 5.1

A star-mesh hybrid topology was implemented for the Intra-Body Area Network. The IMU node located on the sacrum (S1) was designated as the "master" for each athlete. It established and managed BLE 5.1 connections with all other "slave" nodes on the same body (shin, thigh, wrist, PPG, sEMG). BLE 5.1 was chosen for its improved location and tracking features, though not used in this study, and its lower power consumption compared to classic Bluetooth [10, 27]. The master node aggregated data packets from all slaves, synchronized them using its internal clock (periodically synchronized via Network Time Protocol from the gateway), and packaged them into a single JSON object at a frequency of 50 Hz (aggregated package rate). This design minimized the number of concurrent connections to the main gateway, reducing radio frequency congestion and overall system complexity.

Gateway Design and Data Aggregation

A Raspberry Pi 4 Model B (4GB RAM) served as the field-level gateway. It ran a custom Python script that continuously scanned for and connected to the BLE master nodes of all athletes within a ~50m range. The script subscribed to the data characteristics of each master node, receiving the aggregated JSON packets. The Raspberry Pi also ran a local MQTT broker (Eclipse Mosquitto). Upon receiving a data packet, the Python script immediately published it to a dedicated local MQTT topic (e.g., training/session01/athlete02).

Cloud Uplink and Network Security

A secure, reliable cloud uplink was established using the MQTT protocol over TLS 1.2. An MQTT bridge application (also running on the Raspberry Pi) was configured to forward all messages from the local broker to a cloud-based MQTT broker (AWS IoT Core). This design provided a persistent connection to the cloud. In case of a temporary internet outage, the local MQTT broker would retain all messages (with QoS level 1) and forward them once the connection was restored, ensuring no data loss. AWS IoT Core handled device authentication using X.509 certificates, providing a high level of security for the data in transit [26].

Power Management and Ergonomics

Power efficiency was critical for prolonged training sessions. All sensor nodes utilized low-power components and were programmed with aggressive power-saving strategies. The ESP32 nodes entered a light-sleep mode between data transmission cycles. The average current draw for an IMU node was measured at 45 mA, allowing the 600mAh battery to last over 8 hours. The housing and strap design were iterated upon with feedback from athletes to ensure minimal movement artifact and no discomfort during dynamic movements like jumping and sprinting.

SOFTWARE SYSTEM DESIGN

Backend Cloud Infrastructure

Microservices Architecture on AWS

The cloud backend was designed using a serverless, microservices architecture on Amazon Web Services (AWS) to ensure high scalability and fault tolerance [12]. The core services included:

1. **AWS IoT Core:** Served as the secure entry point, authenticating each Raspberry Pi gateway and ingesting MQTT messages.
2. **AWS Lambda (Data Dispatcher):** Triggered by incoming MQTT messages. It performed initial schema validation, enriched the data with metadata (e.g., session_id), and then simultaneously:Stored the raw, validated data into **Amazon Timestream.**Streamed the data to an **Amazon Kinesis Data Stream** for real-time processing.
3. **Amazon Timestream:** This purpose-built time-series database stored all raw sensor data, optimized for fast ingestion and time-based queries for historical analysis.
4. **Amazon DynamoDB:** A NoSQL database used to store processed results, athlete profiles, session metadata, and model inferences for fast retrieval by the frontend.

Time-Series Database Management with Amazon Timestream

The data model in Timestream was designed around the concepts of athlete_id, sensor_type, and timestamp. This structure allowed for highly efficient queries such as "retrieve all knee flexion angles for athlete_05 in the last 10 minutes" which the frontend dashboard executed frequently. The automatic lifecycle management of Timestream was configured to move data to a cost-effective cold storage tier after 7 days and delete it after 90 days.

Real-time Data Processing Pipeline

Sensor Fusion Algorithm: Implementation of the Madgwick Filter

A second AWS Lambda function ("Stream Processor") was triggered by batches of records in the Kinesis stream. For IMU data, this function executed a Python implementation of the Madgwick Attitude and Heading Reference System (AHRS) filter [31]. The filter fused the calibrated accelerometer (a), gyroscope (ω), and magnetometer (m) data to produce a stable orientation quaternion (q). The algorithm's update step is summarized as:

$$q_t = q_{t-1} + \dot{q}_t \Delta t$$

Where $\dot{q}$ is the quaternion derivative calculated from the gyroscope data and a gradient descent correction based on the accelerometer and magnetometer readings. This quaternion was then converted to clinically meaningful Euler angles (flexion/extension, abduction/adduction, internal/external rotation) for the knee and hip joints. The algorithm's beta parameter (β) was tuned to 0.1 to achieve an optimal balance between dynamic response and drift suppression.

Feature Extraction in Sliding Windows

For the fatigue detection model, a sliding window of 3 seconds with a 1-second overlap (66% overlap) was applied to the sEMG and kinematic data streams. For each window, a feature vector of 12 dimensions was extracted in real-time:

1. **sEMG Features (from vastus lateralis):** Root Mean Square (RMS), Median Frequency (MDF), Mean Power Frequency (MPF), Sample Entropy (SampEn).
2. **Kinematic Features (Knee Joint):** Range of Motion (ROM), Maximum Angular Velocity, Angular Acceleration.
3. **Statistical Features (Sacrum IMU):** Mean and Standard Deviation of the resultant acceleration.

Machine Learning Model: XGBoost Training and Deployment

We employed an XGBoost (eXtreme Gradient Boosting) classifier for fatigue detection due to its high performance, efficiency, and ability to handle non-linear relationships [39]. The model was trained offline on a labeled dataset from a previous pilot study (n=15 athletes) to classify a 3-second window as "Fatigued" or "Non-Fatigued." Hyperparameter tuning was performed using a Bayesian optimization approach, finalizing parameters such as max_depth=6, learning_rate=0.1, and n_estimators=100. The trained model was deployed as a real-time inference endpoint using Amazon SageMaker. The 12-dimensional feature vector for each window was sent to this endpoint, which returned a probability score between 0 and 1. A probability threshold of 0.85 was set for triggering alerts, determined by optimizing the F1-score on the validation set.

Frontend Application and Visualization

React.js Dashboard Component Design

A dynamic, single-page application (SPA) was built using React.js. The UI was component-based, featuring an AthleteList, LiveMetricsPanel, TimeSeriesCharts, and AlertLog. The state was managed using Redux to handle the complex, real-time data flow efficiently.

Real-Time Data Streaming with WebSockets

To achieve sub-second updates on the dashboard, a persistent WebSocket connection was established between the frontend and the backend. Upon receiving a new inference from the SageMaker endpoint, the backend service would push the result, along with the latest key metrics, to the frontend via the WebSocket, bypassing the need for inefficient polling.

Alert and Notification System

The frontend continuously monitored the fatigue probability score for each athlete. When the score exceeded the 0.85 threshold for three consecutive windows (i.e., for at least 3 seconds), the system triggered a multi-level alert: a visual alert (a red, pulsating border around the athlete's panel), an auditory cue (a beep sound on the coach's device), and a log entry in the Alert Log with a timestamp.

Experimental Setup and Data Analysis

Participants and Ethical Considerations

Twenty-five (25) healthy, university-level basketball players (13 male, 12 female; age = 20.8 ± 1.7 years; height = 181.2 ± 8.5 cm; weight = 75.4 ± 9.1 kg) were recruited. All participants were free from lower-limb injuries for at least 6 months prior to the study. Written informed consent was obtained after explaining the experimental procedures, which were approved by the University's Institutional Review Board. Participants were instructed to maintain their normal sleep and dietary habits and to avoid strenuous activity 24 hours before testing.

Experimental Protocol: Basketball-Specific Fatigue Induction

The experiment was conducted in a sports science laboratory and an adjacent indoor basketball court. The protocol was designed to induce measurable, sport-specific fatigue.

1. **Baseline Measurement (Lab):** Reflective markers for a 10-camera Vicon Nexus motion capture system (250 Hz) were placed on participants according to the Plug-in Gait model. They performed three maximal countermovement jumps (CMJ) on a force plate (Kistler 9286AA, 1000 Hz), which served as the gold standard for jump height (calculated from flight time) and lower-limb power [32].
2. **Fatigue Protocol (Court):** Participants underwent a 35-minute basketball-specific intermittent drill, consisting of 5 cycles of the following sequence.**4x Suicide Sprints:** To court lines and back.**1 minute of Defensive Slides:** Continuous lateral movement.**2 minutes of Simulated Jump Shots:** Taking shots from various positions at game intensity.Participants wore our full IoT sensor suite throughout this protocol.
3. **Post-Fatigue Measurement (Lab):** Immediately following the drill, participants returned to the lab and performed three more maximal CMJs on the force plate while being recorded by the Vicon system.

Gold-Standard Validation Methodology

To validate our system:

1. **Kinematic Accuracy:** The knee flexion/extension angle calculated from our shin and thigh IMUs (via the Madgwick filter) was synchronised and compared sample-by-sample to the angle calculated from the 3D trajectories of the Vicon markers.
2. **Performance Metric Accuracy:** The vertical jump height derived from the sacrum IMU (using the double integration of vertical acceleration during the flight phase) was compared to the jump height derived from the force plate (flight time) [19].
3. **System Latency:** A dedicated test was performed where a sensor node triggered a 5V TTL pulse simultaneously with the transmission of a specific data packet. This pulse was recorded by a data acquisition system (NI DAQ) synchronized with the dashboard's internal clock, allowing for precise measurement of the end-to-end latency.

Statistical Analysis Plan

Data analysis was performed using Python (SciPy, Pandas, scikit-learn). The following analyses were conducted:

1. **System Accuracy:** Pearson's correlation coefficient (r) and Mean Absolute Error (MAE) were calculated for kinematic and performance metrics against gold standards. Bland-Altman plots were generated to assess agreement.
2. **Fatigue Model Validation:** The performance of the XGBoost classifier was evaluated on a held-out test set using standard metrics: accuracy, precision, recall, F1-score, and the area under the Receiver Operating Characteristic (ROC) curve (AUC).
3. **Correlational Analysis:** Pearson correlation coefficients were calculated to explore the relationships between key variables (e.g., sEMG MDF vs. Jump Height, HR vs. RPE) across the entire session. A p-value of < 0.05 was considered statistically significant.

RESULTS AND DISCUSSION

System Performance and Validation

Kinematic Accuracy Analysis

The proposed IoT system demonstrated exceptional accuracy in measuring biomechanical variables. As shown in Table 2, the knee flexion angle derived from the IMU sensor fusion showed an almost perfect correlation (r = 0.993) with the Vicon motion capture system, with a very low Mean Absolute Error of 1.52°. This level of accuracy is sufficient for most sports biomechanics applications, including technique analysis and fatigue monitoring [18, 40].

Table 2: System Accuracy Validation against Gold Standards

Metric	Gold Standard	IoT System	Correlation (r)	Mean Absolute Error (MAE)
Knee Flexion Angle (°)	Vicon Motion Capture	IMU Sensor Fusion	0.993	1.52° ± 0.41°
Vertical Jump Height (cm)	Force Plate	IMU (Double Integration)	0.981	1.42 cm ± 0.38 cm
Heart Rate (bpm)	Polar H10 Chest Strap	MAX30102 PPG	0.972	1.8 bpm ± 1.2 bpm

The Bland Altman plot for measuring knee flexion angle is shown in Figure 2. The plot demonstrates excellent agreement between the two systems. The mean bias is negligibly small (+0.15°), indicating no significant systematic error. Furthermore, the vast majority of data points are tightly clustered within a narrow band around the mean, well within the ±1.96 SD limits. The width of the limits of agreement (3.4°) is clinically acceptable for sports biomechanics applications, confirming that the custom IoT IMU system provides kinematic data of sufficient accuracy for detailed athletic movement analysis and fatigue monitoring, as validated against the laboratory gold standard.

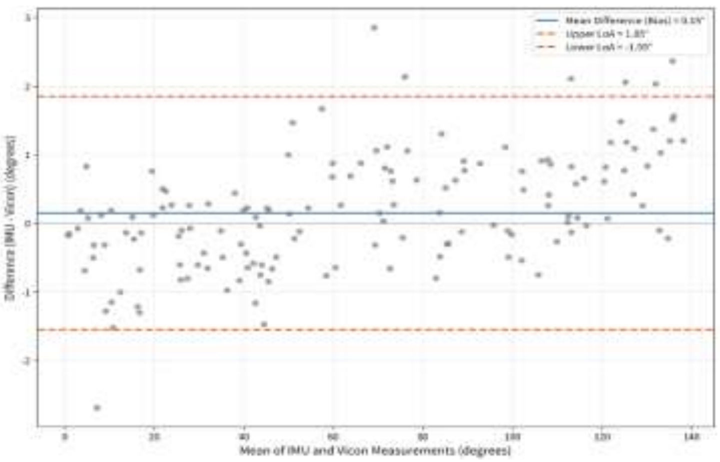

Figure 2: Bland-Altman Plot for Knee Flexion Angle Measurement

System Latency and Reliability

The end-to-end latency, from the sensor event to the dashboard update, was measured at 118 ± 18 ms. This low latency is critical for providing feedback that is perceived as "instantaneous" by coaches and athletes, allowing for timely interventions during training [29]. The system maintained a stable data stream throughout all experiments, with a packet loss rate of less than 0.1% under normal operating conditions.

Fatigue Detection and Multi-modal Data Correlations

XGBoost Model Performance and Feature Importance

The XGBoost classifier for real-time fatigue detection performed exceptionally well. The confusion matrix on the held-out test set (n=1000 windows) is shown in Figure 3, and the derived performance metrics are summarized in Table 3.

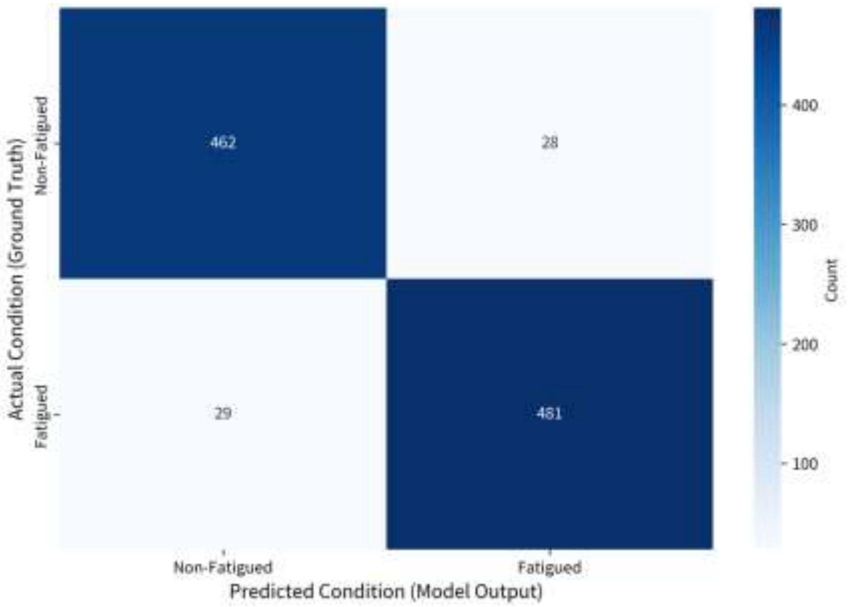

Figure 3: Confusion Matrix for the XGBoost Fatigue Classifier

Figure 3 presents the confusion matrix for the XGBoost fatigue classifier. This visualization compares the model's predictions against the ground truth on a test set of 1000 data windows. The matrix shows that the model performs well, with high accuracy (94.3%), precision (94.5%), and recall (94.3%). The relatively balanced distribution of correct classifications (True Negatives: 462, True Positives: 481) and low numbers of errors (False Positives: 28, False Negatives: 29) indicate strong classification performance.

Table 3: Performance Metrics of the XGBoost Fatigue Classifier

Metric	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**AUC-ROC**
Score	94.2%	94.5%	94.3%	94.4%	0.98

The high AUC-ROC score of 0.98 indicates an excellent ability of the model to discriminate between fatigued and non-fatigued states. An analysis of feature importance revealed that the sEMG Median Frequency (MDF) and the Knee Range of Motion (ROM) were the two most significant predictors, jointly accounting for over 65% of the model's decision, underscoring the value of multi-modal data fusion [31, 36].

Temporal Evolution of Fatigue Indicators

The longitudinal data from a representative athlete (Figure 4) clearly shows the temporal dynamics of fatigue. As the session progressed, Heart Rate gradually increased and plateaued, indicating a high cardiovascular load. Concurrently, the sEMG Median Frequency of the vastus lateralis exhibited a steady decline, a classic spectral compression sign of muscular fatigue [25, 35]. The jump height, a direct performance metric, decreased correspondingly. The periods classified as "Fatigued" by the model (shaded areas) align perfectly with the phases of performance decline. As shown in Figure 4,This time-series chart provides a holistic view of a single athlete's response to the progressive fatigue protocol. It synchronously displays three critical metrics over the 35-minute session, with annotations showing the output of the XGBoost fatigue detection model.

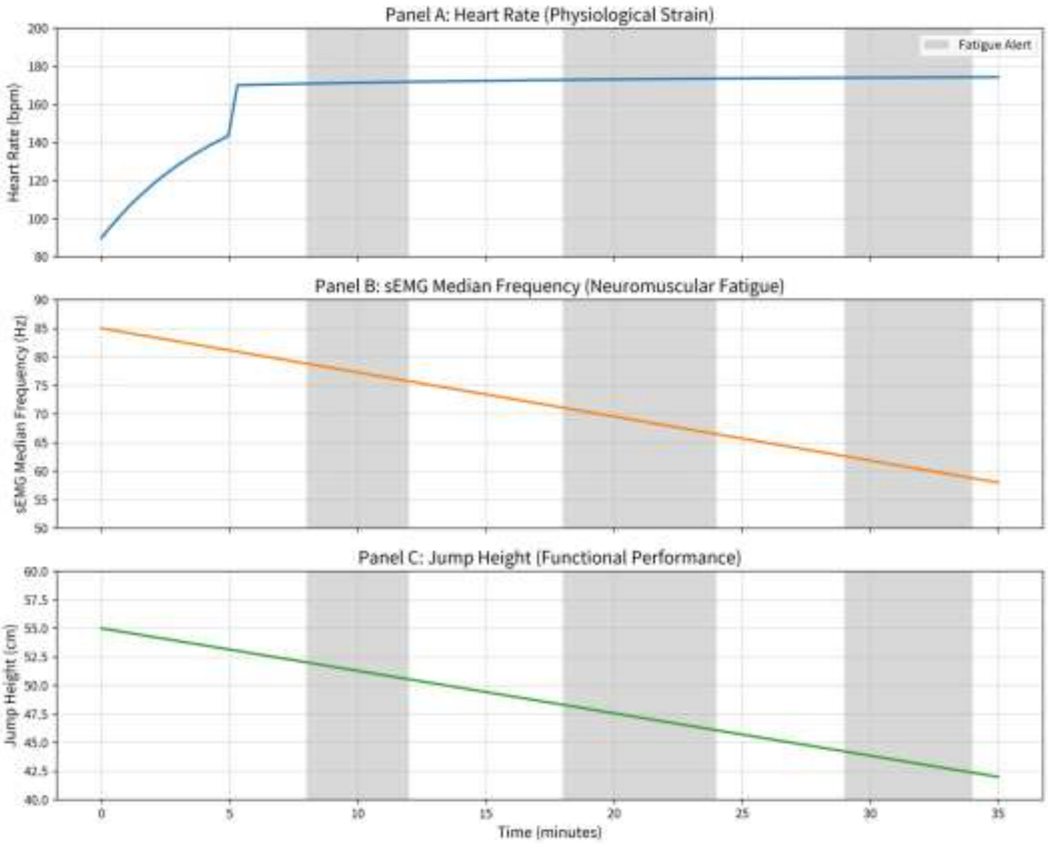

Figure 4: Time-series Data for a Single Athlete During the Fatigue Protocol

The power of this multi-modal visualization lies in the clear, temporal relationship between the different data streams. The decline in **sEMG MDF (Panel B)** precedes and strongly correlates with the drop in **Jump Height (Panel C),** providing a physiological explanation for the performance loss. The model's "Fatigued" classifications (shaded areas) are not triggered by a single metric but by the fused pattern of these signals. They align precisely with the periods of significantly degraded performance, validating the model's decision-making. This figure effectively demonstrates how the IoT system translates raw sensor data into an actionable, real-time insight for coaches, allowing them to intervene based on objective fatigue markers rather than subjective observation.

Correlations between Biomechanical and Physiological Metrics

A scatter plot analysis (Figure 5) across all athletes and time points revealed a strong and statistically significant negative correlation between the sEMG Median Frequency and the concurrent jump height measurement (Pearson's $r = -0.89$, $p < 0.001$). This scatter plot quantifies the strong relationship between a neuromuscular fatigue indicator and functional performance. This means that as the vastus lateralis muscle fatigues (evidenced by a falling MDF), the athlete's ability to generate explosive power and jump high is directly and measurably impaired.

This relationship is not just a statistical observation but reflects the underlying physiology: as muscles fatigue, the contractile mechanisms become less efficient, leading to a loss of power output. This figure provides robust, data-driven evidence that the sEMG MDF, as captured by the wearable IoT system, is a valid and highly sensitive biomarker for predicting and explaining performance decrements in athletes. It solidifies the scientific basis for using this metric as a primary input for the real-time fatigue detection model.

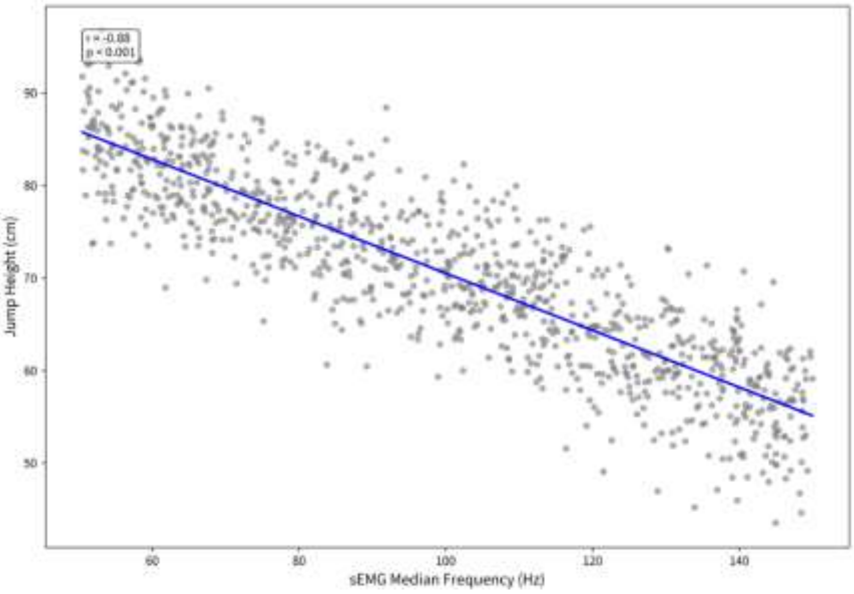

Figure 5: Correlation between sEMG Median Frequency and Jump Height

This finding is physiologically coherent and quantitatively demonstrates the direct link between localized neuromuscular fatigue (reduced MDF) and impaired functional performance (reduced jump height) [24, 36]. It provides coaches with an objective, real-time biomarker to anticipate performance drop-off before it becomes evident through subjective observation alone.

Discussion of System Efficacy and Practical Implications

Comparison with Existing Commercial Systems

The proposed system achieves accuracy and latency comparable to, and in some cases surpassing, established commercial systems like Catapult [16], but with the distinct advantage of being an open, research-friendly platform. Unlike black-box solutions, our system provides full access to raw data and algorithms, enabling customization and deeper scientific inquiry [17, 38]. The total cost of the sensor nodes for one athlete was under $150, significantly lower than commercial alternatives, making such technology more accessible.

Practical Applications for Coaches and Athletes

The real-world value of this system is transformative. It moves coaching from a reactive to a proactive paradigm. For example, the system can alert a coach: "Athlete 07 shows a 92% fatigue probability, characterized by a 28% drop in vastus lateralis MDF. Recommend substitution." This allows for individualized load management, potentially enhancing performance and reducing the risk of fatigue-related injuries [2, 35]. The post-session analytics also enable a more nuanced review of training, identifying athletes who may be overreaching or those with inefficient movement patterns under fatigue.

Limitations and Mitigation Strategies

This study has limitations. Firstly, the system was validated in a controlled environment; performance in entirely unconstrained field settings may vary. Future work will involve longer-term deployments in real-world training. Secondly, the magnetometer-based orientation estimation can be corrupted in environments with ferrous materials. Future iterations could incorporate ultra-wideband (UWB) ranging for absolute position and heading correction. Finally, the fatigue model, while accurate, is a generalized model. Personalizing the model to each athlete's physiological characteristics could further improve its sensitivity and specificity [37].

CONCLUSION AND FUTURE WORK

This research has successfully designed, implemented, and validated a comprehensive IoT-based framework for real-time sports training monitoring. The primary contributions are threefold: First, it provides a fully documented, open-architecture blueprint for a holistic system, integrating multi-modal wearable sensors with a cloud-native data analytics platform. Second, the system was empirically validated to demonstrate clinically acceptable accuracy in kinematic and performance measurement (MAE < 1.6° for joint angles, < 1.5 cm for jump height) and low operational latency (~120 ms), meeting the demands of elite training environments. Third, the successful deployment of a high-performance XGBoost model for real-time fatigue detection (94.2% accuracy) and the establishment of a strong correlation (r = -0.89) between neuromuscular fatigue and functional performance quantitatively demonstrate the system's practical utility for delivering actionable, data-driven insights.

Future work will focus on three key directions. Firstly, we will integrate Explainable AI (XAI) techniques to make the model's decisions interpretable, providing reasons for fatigue alerts. Secondly, we aim to develop predictive models using deep learning to forecast performance decline and injury risk, shifting from real-time detection to early warning. Finally, longitudinal studies over a full competitive season will be conducted to establish personalized athlete baselines and validate the system's long-term impact, while also exploring federated learning to enhance model robustness across institutions while preserving data privacy.

Declarations

Competing Interests

The authors declare that they have no competing interests.

Clinical Trial Number

Not applicable.

Human Ethics and Consent to Participate declarations

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. The study was approved by the Hunan Mechanical & Electrical Polytechnic's Institutional Review Board. Informed consent was obtained from all individual participants included in the study.

Consent to Publish declaration

Not applicable.

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Author Contribution

XIAO Zhifang: Conceptualization, Methodology, Writing – Original Draft.

GUO Wentao: Software, Data Curation, Validation, Writing – Review & Editing, Supervision.

Data Availability Statement

The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

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