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Design and Efficacy Study of a Digital Sports Training System Based on Smart Textiles

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Article

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ABSTRACT

Smart textiles represent a paradigm shift in wearable technology, enabling the seamless integration of multimodal sensing capabilities directly into apparel for complex human performance analysis. This paper presents the design, implementation, and efficacy evaluation of a novel digital sports training system centered on a smart textile garment. The system architecture features: (1) a sensor-integrated garment for real-time collection of biomechanical and physiological data; (2) a wireless data acquisition module; and (3) a software platform for data analysis and actionable feedback. The smart garment incorporates a network of flexible piezoresistive sensors and inertial measurement units (IMUs) for motion and pressure capture, alongside textile-based electrodes for electrocardiogram (ECG) and electromyography (EMG) monitoring. A six-week controlled study involving amateur basketball players was conducted. The experimental group (EG), using the smart textile system, demonstrated statistically significant improvements in shooting form consistency (18.5% increase, $p < 0.01$) and vertical jump height (8.2% increase, $p < 0.05$) compared to the control group (CG). This study provides strong evidence for the effectiveness of smart textile-based systems in providing quantitative, real-time, and personalized feedback, suggesting that such systems may be a powerful tool for enhancing athletic training outcomes.

KEYWORDS

smart textiles, wearable sensors, sports biomechanics, performance analysis, digital sports

INTRODUCTION

Traditional sports training has long relied on the qualitative assessment of experienced coaches and post-session video analysis [1]. While invaluable, these methods often suffer from subjectivity, delayed feedback, and limited ability to capture the intricate, simultaneous interplay between an athlete's biomechanics and physiological state during performance [2,3]. Although the advent of digital technology promised a new era of data-driven sports science, initial solutions struggled to deliver on this potential in practical training environments. These early systems, which typically involved cumbersome lab-based equipment or single-point wearable devices, suffered from limited ecological validity and failed to capture natural athletic movements in a real-world context [4,5].

The emergence of smart textiles—fabrics integrated with electronic elements and sensors—offer a revolutionary solution to this challenge [6]. By embedding sensing capabilities directly into the fabric of athletic apparel, it becomes possible to create a “second skin” that can continuously and unobtrusively monitor an athlete’s performance [7]. These systems can capture a rich, multimodal dataset, encompassing both the “how” (kinematics and kinetics) and the “why” (physiological exertion) of athletic performance [8]. This integrated approach is crucial, as optimal athletic form is often a delicate balance between efficient movement and managed physiological stress. For instance, a decline in shooting accuracy in basketball may be due to a subtle change in elbow extension (a biomechanical factor) or muscular fatigue (a physiological factor), and distinguishing between the two is essential for effective intervention [9,10].

Despite the promise, the transition from prototype smart garments to a comprehensive, validated digital training system presents significant scientific and engineering challenges [11]. These include sensor selection and integration for durability and comfort, robust data acquisition and noise filtering algorithms, and the development of a software platform that translates raw data into meaningful, actionable insights for athletes and coaches [12]. Furthermore, rigorous scientific validation of such systems is required to prove their efficacy compared to traditional training methods.

This paper addresses these challenges by presenting a complete, end-to-end digital sports training system based on smart textiles. The research has three primary objectives: (1) to design and implement an integrated system featuring a multi-sensor smart garment, a wireless data transmission unit, and an analytical software platform; (2) to develop a methodology for processing and analyzing multimodal data to generate key performance indicators (KPIs) relevant to complex athletic tasks; and (3) to conduct a controlled experimental study to scientifically evaluate the efficacy of the system in improving athletic performance compared to a traditional training regimen. For our study, we focus on basketball as a use case, given its dynamic nature involving complex biomechanical movements (jumping, shooting) and significant physiological demands.

SYSTEM DESIGN AND ARCHITECTURE

The proposed Digital Sports Training System is a multi-layered architecture designed for real-time data collection, processing, and feedback. Figure 1 provides a schematic overview of this architecture. It consists of the smart textile garment, the data acquisition and transmission (DAT) module, and the software and analytics platform.

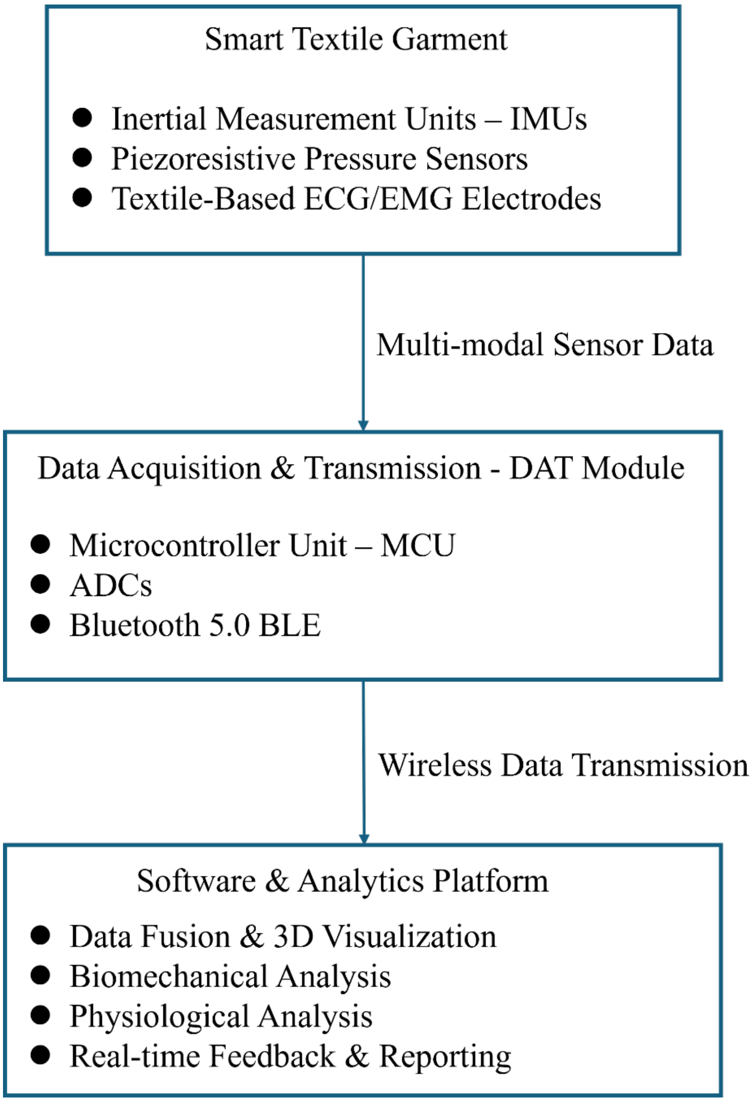

Figure 1. System Architecture of the Digital Sports Training System

The Smart Textile Garment

The foundation of the system is a form-fitting, moisture-wicking compression shirt and tights made from a blend of nylon and spandex. This base material ensures comfort, durability, and close skin contact for optimal sensor readings. The following sensors are integrated into the garment:

- Inertial Measurement Units (IMUs): Ten 9-axis IMUs (comprising an accelerometer, gyroscope, and magnetometer) are strategically embedded within the garment to capture full-body kinematics. Specifically, we used the Bosch Sensortec BNO055, a system-in-package solution that integrates a triaxial 14-bit accelerometer, a 16-bit gyroscope with a range of ±2,000°/s, and a triaxial geomagnetic sensor, providing a high degree of accuracy for motion tracking. They are placed according to key anatomical landmarks (e.g., sternum, lumbar spine, upper arms, thighs, shanks) to reconstruct a 3D skeletal model of the athlete. The IMUs were housed in lightweight, flexible silicone pods sewn into the fabric to prevent discomfort and ensure consistent positioning.
- Piezoresistive Pressure Sensors: A flexible matrix of 64 piezoresistive sensors is integrated into the soles of accompanying smart socks, connected wirelessly to the main DAT module. The sensor matrix was constructed using Tekscan FlexiForce™ A201 sensors. Given the sensors' low dynamic force range, they were not used to approximate ground reaction forces. Instead, they functioned as binary contact switches to precisely detect the moments of takeoff and landing. The high sensitivity of the sensors allowed for reliable detection of initial ground contact and final ground departure. These sensors map the dynamic pressure distribution of the foot during movements like jumping and landing. This provides data on balance, and weight transfer, which are critical for analyzing jump mechanics and agility.
- Textile-Based Electrodes: We utilized silver-coated conductive yarns woven directly into the fabric to create textile electrodes.
  - Electrocardiogram (ECG): A three-lead ECG configuration is integrated into the chest area of the shirt to continuously monitor heart rate (HR) and heart rate variability (HRV). This provides a reliable measure of cardiovascular load and recovery status.
  - Electromyography (EMG): Surface EMG (sEMG) electrodes are woven into the fabric over major muscle groups involved in the target sport, such as the pectoralis major and triceps for shooting, and the quadriceps and gluteus maximus for jumping. These sensors measure the electrical activity of muscles, providing insights into muscle activation patterns, fatigue, and muscle group coordination.

All wiring is accomplished using flexible, insulated conductive threads, which are embroidered into the garment in a way that allows for natural fabric stretch and movement. To ensure the comfort of the athletes and minimize the impact on their performance, all sensor modules are encapsulated in a flexible form and embedded into the key nodes of the clothing, avoiding the creation of rigid points in the main joint movement areas. The DAT module is designed to operate with low power consumption. During continuous use, the temperature rise of its outer shell is controlled within 2 °C above the body surface temperature, without causing discomfort.

Data Acquisition and Transmission (DAT) Module

The DAT module is the central hub for data collection and communication. It is a compact, lightweight (85 g) unit housed in a protective casing, worn securely at the athlete's lower back. Its key components are:

- Microcontroller Unit (MCU): An ARM Cortex-M4-based MCU is used for its processing power and low energy consumption. It synchronizes and samples data from all integrated sensors. IMU data were sampled at 100 Hz, pressure sensor data at 50 Hz, and ECG/EMG data at 500 Hz.
- Analog-to-Digital Converters (ADCs): High-resolution 24-bit ADCs are used to digitize the analog signals from the pressure, ECG, and EMG sensors, ensuring high-fidelity data.
- Wireless Communication: A Bluetooth Low Energy (BLE) 5.0 module transmits the collected data in real-time to a nearby base station (a laptop or tablet) running the system's software platform. The software platform was developed to be compatible with standard modern computing hardware. For the purposes of this study, the base station used was a laptop equipped with an Intel Core i7 processor, 16 GB of RAM, and running the Windows 11 operating system, which was sufficient to handle real-time data processing and visualization without noticeable latency. BLE is chosen for its low power consumption, which allows for a battery life of over 4 hours of continuous use. To ensure the integrity of the real-time feedback loop, several measures were taken to address potential data loss and latency. The DAT module's firmware includes a small data buffer to handle transient connection drops, and the BLE 5.0 protocol's adaptive frequency hopping helps mitigate interference from other 2.4 GHz devices. During the study, the base station was kept within a 10 m line of sight of the athlete, ensuring a consistently stable and low-latency connection.
- Power Management: The module is powered by a rechargeable lithium-polymer battery.

Software and Analytics Platform

The software platform is the user-facing component that transforms raw sensor data into actionable intelligence. It features a graphical user interface (GUI) designed for both athletes and coaches. Its functionalities include:

- Data Synchronization and Fusion: The platform receives data streams from the DAT module and performs temporal synchronization. It then fuses data from the IMUs using the Madgwick algorithm or a similar sensor-fusion algorithm to create a real-time three-dimensional (3D) avatar of the athlete. To provide full control over the data processing pipeline, we configured the BNO055 sensors to operate in a non-fusion mode, which outputs only the raw, calibrated data from the integrated accelerometer, gyroscope, and magnetometer. This approach allowed us to bypass the sensor's internal fusion engine and implement a consistent Madgwick algorithm across all IMUs. The algorithm was implemented with a gain parameter (β) of 0.041, a value determined empirically to provide an optimal balance between responsiveness and noise filtering for dynamic basketball movements. To address magnetic interference, a standard ellipsoid-fitting calibration routine was performed for each sensor in the training environment prior to data collection. The Madgwick algorithm inherently uses the accelerometer data to correct for roll and pitch drift and the calibrated magnetometer data to correct for yaw drift, ensuring stable orientation tracking over the duration of the training sessions.
- Biomechanical Analysis Module: This module calculates key biomechanical KPIs. For basketball shooting, it calculates the joint angles at the elbow and wrist during the shooting motion, the release height, and the shot trajectory. The system assesses "Form Consistency" using a two-stage process. First, an individual "optimal profile" is established for each athlete during a baseline calibration session. In this session, the coach identifies several of the athlete's most successful shots, and the system calculates the mean and standard deviation of key biomechanical parameters (e.g., elbow extension angle at release, shot release height) from these ideal attempts. This data-driven range is defined as the athlete's "optimal range." Subsequently, for each new shot, the algorithm calculates a deviation score based on the Mahalanobis distance from the mean of that optimal profile, which accounts for correlations between different variables. The Form Consistency KPI is then quantified as the inverse of the coefficient of variation of these deviation scores across a series of shots, rewarding lower variability with a higher score. For jumping, it calculates vertical jump height from the flight time (derived from foot pressure sensor data) and analyzes landing impact forces.
- Physiological Analysis Module: This module processes ECG and EMG data. It calculates real-time HR and HRV to quantify cardiovascular strain. The Training Load score is calculated using a TRIMP-based algorithm (training impulse). EMG data were processed to analyze muscle activation and fatigue. The raw sEMG signals were first processed with a band-pass filter between 20–200 Hz and a 50 Hz notch

filter to remove powerline interference. To assess muscle fatigue, the median frequency (MDF) of the EMG power spectrum was calculated. This was done using a short-time Fourier transform (STFT) with a 256-sample Hamming window and 50% overlap, and the MDF was tracked over the duration of the activity.

- Real-time Feedback and Visualization: The GUI displayed the 3D avatar, real-time KPIs, and physiological data. It provided immediate feedback to the athlete. For example, if a player's elbow extension angle deviates from their optimal range during a shot, a visual or auditory alert can be triggered.
- Post-Session Reporting: After a training session, the platform generated a comprehensive report summarizing performance trends, highlighting areas for improvement, and providing a longitudinal view of the athlete's progress and training load.

RESEARCH METHODOLOGY

To validate the efficacy of the digital sports training system, a six-week controlled intervention study was conducted.

Participants

Thirty healthy male amateur basketball players (age: 22.4 ± 2.8 years; height: 185.6 ± 5.1 cm; experience: 4.5 ± 1.2 years) were recruited. Participants provided informed consent, and the study was approved by the Institutional Review Board. Data privacy and security were strictly maintained throughout the study. All collected data were immediately anonymized using a unique participant code, and all identifiable information was removed. The dataset was stored on a secure, encrypted server with access limited to the core research team to ensure confidentiality. These data handling procedures were compliant with all institutional and relevant data protection regulations. They were randomly assigned to one of two groups: an experimental group (EG, n = 15) that would use the smart textile system, or a control group (CG, n = 15) that would follow a traditional training program. The random allocation sequence was generated by a researcher not involved in the participant recruitment or training, using a computerized random number generator (SPSS v 26.0).

Experimental Protocol

All participants underwent a pre-test (Week 0) and a post-test (Week 6) to assess baseline and final performance. The tests included:

- A standardized basketball shooting test (50 free throws) to measure accuracy and form.
- A vertical jump test (countermovement jump) to measure explosive power.
- An agility T-test to measure speed and change-of-direction ability.

During the six-week intervention period, both groups participated in three 90-minute training sessions per week. The content of the sessions (drills, conditioning) was identical for both groups. Attendance for all training sessions was mandatory and monitored; both groups demonstrated high compliance, with no significant difference in the overall attendance rate (EG: 98.8% vs. CG: 97.9%, $p > 0.05$).

- CG: Received coaching feedback based on visual observation and post-session video review with the coach.
- EG: Wore the smart textile system during all training sessions. They received real-time feedback from the system's software platform on key aspects of their form (e.g., shooting arm angles, jump symmetry) and physiological status. Coaches for the EG were trained to use the system's data to provide more targeted, quantitative feedback during and after sessions.

Data Collection and Analysis

For the EG, data were collected continuously during all sessions using the smart textile system. For both groups, performance data (shooting accuracy, jump height, agility time) was collected during the pre- and post-tests.

The following KPIs were central to the analysis:

- Shooting Form Consistency: This multivariate KPI was calculated as detailed in Section 2.3, using the Mahalanobis distance to quantify each shot's deviation from an athlete's optimal form.
  - Variable Set: The key biomechanical variables included in the calculation were: 1) elbow extension angle at release, 2) shoulder flexion angle at release, 3) wrist snap velocity, and 4) vertical ball release height.
  - Covariance and Scaling: The mean vector and the sample covariance matrix for these variables were estimated from the athlete's successful shots during their initial calibration session. The Mahalanobis distance is powerful because it is scale-invariant and normalizes for variance and covariance. Therefore, no separate data standardization process was required, as the method inherently handles the different units (e.g., degrees, m/s, meters) and the inter-correlation between the variables. The final KPI was then calculated as the inverse of the coefficient of variation of these

Mahalanobis distance scores across the 50 test shots, with a higher value indicating better consistency.

- Vertical Jump Height: Calculated from flight time measured by the pressure-sensitive socks. The flight time was determined using a threshold-based algorithm on the aggregated signal from the 64 pressure sensors. Takeoff was registered as the first time sample where the total signal dropped below a predefined noise-floor threshold, and landing was registered as the first sample where the signal exceeded it. To prevent spurious triggers from minor movements, a 30 ms anti-jitter filter was applied, requiring the contact/no-contact state to be maintained for at least three consecutive samples.
- Agility T-Test Time: Measured using electronic timing gates.

Physiological Monitoring for Intervention: For the EG, physiological data (HR, HRV, EMG) was monitored in real-time. These data were not used for statistical group comparison but rather to provide the coaching staff with objective insights to guide individualized feedback and adjust training intensity on a case-by-case basis, as detailed in Section 4.2.

Statistical analysis was performed using SPSS. An independent samples t-test was used to compare the baseline performance of the two groups. A two-way mixed ANOVA (Group [EG vs. CG] × Time [Pre vs. Post]) was used to analyze the intervention effects on the primary performance metrics. Statistical significance was set at $p < 0.05$.

RESULTS

At baseline, there were no statistically significant differences between the EG and CG for key demographic characteristics (age, height, years of basketball experience) or any of the performance metrics ($p > 0.05$ for all comparisons), indicating successful randomization and group equivalence prior to the intervention. The primary results of the six-week intervention, comparing the performance changes between the two groups, are presented in Table 1. The results of the six-week intervention are summarized below.

Table 1. Pre- and Post-Intervention Results of Key Performance Indicators for Experimental and Control Groups

Performance Metric	Group	Pre-Test (Mean ± SD)	Post-Test (Mean ± SD)	(% Change)	P value
Shooting Form Consistency (a.u.)	EG	0.76 ± 0.12	0.90 ± 0.11	+18.5%	< 0.01**
	CG	0.75 ± 0.13	0.77 ± 0.14	+2.7%	> 0.05
Vertical Jump Height (cm)	EG	61.2 ± 5.5	66.2 ± 5.3	+8.2%	< 0.05*
	CG	60.8 ± 5.9	62.1 ± 5.8	+2.1%	> 0.05
Shooting Accuracy (%)	EG	68.5 ± 6.2	74.1 ± 8.9	+8.2%	> 0.05
	CG	67.9 ± 6.5	71.8 ± 6.1	+5.7%	> 0.05

Biomechanical Performance

The mixed ANOVA revealed a significant interaction effect between Group and Time for Shooting Form Consistency (F (1, 28) = 8.76, p = 0.006) and Vertical Jump Height (F (1, 28) = 5.21, p = 0.03).

- Shooting Form Consistency: As shown in Figure 2, the EG demonstrated a significant improvement of 18.5% from pre-test to post-test. The CG showed a minor, non-significant improvement of 2.7%.

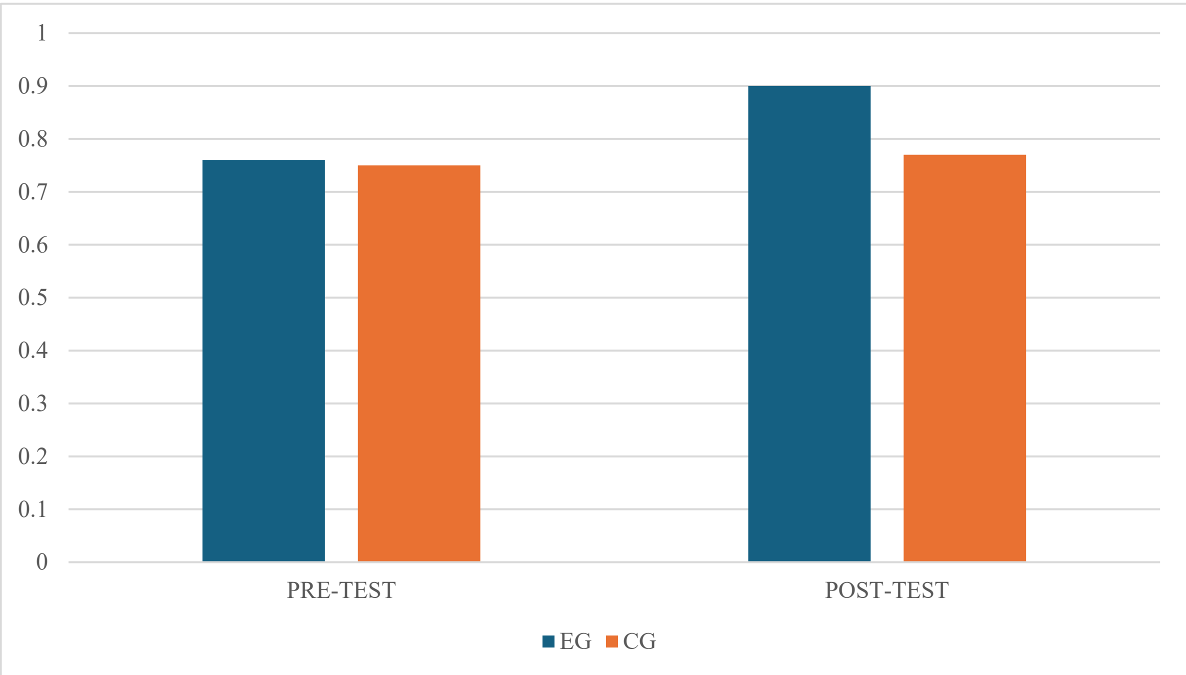

Figure 2. The comparison of the consistency of shooting forms between the EG and the CG before and after the experiment

- Vertical Jump Height: The EG increased their average vertical jump height by 8.2% (from 61.2 cm to 66.2 cm), a statistically significant improvement. The CG's improvement was 2.1% (from 60.8 cm to 62.1 cm), which was not statistically significant.
- Shooting Accuracy and Agility: Both groups showed improvements in shooting accuracy and agility time, but the interaction effect for these metrics was not statistically significant ($p > 0.05$). Although the EG showed a greater trend in shooting accuracy improvement (+8.2%) compared to the CG (+5.7%), it is possible the study was not sufficiently powered to detect a statistically significant difference within the six-week timeframe.

Physiological Monitoring

The data collected from the EG's smart garments allowed for detailed analysis of training load. For instance, EMG data revealed that two players in the EG were over-activating their shoulder muscles (deltoids) as compensation for triceps fatigue late in shooting drills. This insight allowed the coach to assign targeted strengthening exercises. Furthermore, HRV data helped in adjusting the training intensity for individual athletes, preventing potential overtraining. This real-time monitoring allowed for specific, data-driven coaching interventions. Table 2 presents illustrative examples of how these physiological insights were applied to individual athletes during the study.

Table 2. Examples of Individualized Interventions Based on Physiological Monitoring Data

Data source	Affected athletes	Physiological Insights	Corresponding intervention measures
EMG	Two players in the experimental group	In the later stage of the shooting practice, in order to compensate for the fatigue of the triceps, the shoulder (deltoid) muscles were over-activated.	The coach arranged targeted strength-building training.
HRV	Some individual athletes	The data can help adjust the intensity of individual training to prevent potential overtraining.	The training intensity was adjusted for the specific athlete.

DISCUSSION

This study successfully designed, implemented, and validated a Digital Sports Training System based on smart textiles. The results of our controlled experiment provide strong evidence for the system's efficacy in enhancing specific aspects of athletic performance.

The most significant finding is the substantial improvement in biomechanical consistency and explosive power for the EG. The 18.5% improvement in shooting form consistency for the EG is particularly noteworthy. We attribute this directly to the real-time, quantitative feedback provided by the system. While a coach can tell a player their "arm was a bit off," the system can provide objective data, such as "your elbow extension was 175 degrees, 5 degrees short of your optimal 180." This precise, immediate feedback loop accelerates motor learning by allowing athletes to make immediate, conscious corrections and develop a more stable motor pattern. This finding aligns with established theories of motor learning, which emphasize the importance of immediate and accurate knowledge of results for skill acquisition.

Similarly, the significant increase in vertical jump height in the EG can be linked to the feedback from the integrated pressure sensors and IMUs. The system provided athletes with data on their weight distribution during the countermovement phase and the symmetry of their leg drive, allowing them to optimize their jump mechanics for maximum power output. The CG, lacking this detailed information, relied on more general coaching cues, resulting in less significant gains.

It is interesting to note that while consistency and power improved significantly, the differences in overall shooting accuracy and agility between the groups did not reach statistical significance. Although a positive trend was observed for shooting accuracy in the EG, it is possible that the study's duration or sample size was insufficient to yield a statistically significant effect. Shooting accuracy is a multi-factorial skill that also depends on psychological factors, and a six-week intervention may not be long enough to see a transfer from improved form to dramatically improved results. Likewise, the agility test is a measure of gross motor skill, which may be less sensitive to the fine-tuned biomechanical feedback our system provides compared to a discrete technical skill like shooting. From a scientific standpoint, the integration of both biomechanical and physiological sensors in a single, unobtrusive garment is a key contribution of this work. The ability to correlate a drop in mechanical efficiency (e.g., reduced jump height) with a concurrent physiological indicator (e.g., EMG-detected muscle fatigue or high HRV-derived stress) provides a holistic view of the athlete. This allows for more intelligent training load management, helping to distinguish between a technical error and a physical limitation, and thus preventing injury and overtraining.

A primary and significant limitation of this study is the absence of a dedicated validation experiment to confirm the accuracy and reliability of our system against gold-standard laboratory equipment. While the study demonstrates the system's potential to effect change in athletic performance, the absolute accuracy of the collected data—such as vertical jump height derived from pressure sensors, which was not compared to a force plate, or HR data from our textile electrodes, which was not validated against a medical-grade ECG or commercial HR monitor—has not been established. Therefore, while the observed performance changes are meaningful within the context of this intervention, the absolute values of the reported metrics should be interpreted with caution. A rigorous validation study must be a prerequisite for future research using this system.

This study has several limitations that should be acknowledged. Additionally, a notable limitation exists in our EMG data acquisition and analysis. The EMG data were sampled at 500 Hz, which is considered the minimum rate for frequency domain analysis and is susceptible to aliasing, potentially affecting the accuracy of the MDF calculations used for fatigue assessment. Future studies should employ a higher sampling rate (≥1,000 Hz) and provide a more comprehensive validation of electrode placement and test-retest reliability to ensure the robustness of physiological conclusions. The relatively small sample size (n = 30) and the exclusive focus on amateur basketball players may limit the generalizability of our findings to other populations. Furthermore, this study failed to provide data on the long-term durability of smart clothing after multiple washing cycles, which is a key factor that needs to be evaluated before commercialization. We also did not quantify the possible sensor positioning errors introduced each time the clothing is worn or taken off; although the clothing design aims to ensure consistency, assessing this potential inter-session variability is crucial for longitudinal studies that require high-precision biomechanical analysis. Whether similar gains would be observed in elite or professional athletes, who may have more ingrained motor patterns, remains an open question. Therefore, future work should aim to validate these results with larger, more diverse cohorts, including athletes from different sports and varying skill levels. Future research should involve longer-term longitudinal studies to observe the translation of improved mechanics into long-term performance gains. Furthermore, expanding the system's application to other sports (e.g., running, golf, swimming) would require the development of new sport-specific KPIs and analytical modules. The durability of the smart garments over many months of use and washing cycles also requires further investigation. A significant limitation of the current study is the method for determining vertical jump height. The use of low-range piezoresistive sensors as binary contact switches, while effective for timing, is susceptible to error from signal noise and does not allow for the analysis of ground reaction forces or landing impact. The sensor saturation upon contact prevents any analysis of force distribution or magnitude. While the thresholding strategy was designed to be robust, future iterations of the system must incorporate high-range pressure sensors or insoles to allow for kinetic analysis and to validate jump height against a force plate, thereby increasing the reliability of this key performance metric. Furthermore, while physiological monitoring provided valuable data for individualized coaching, this study reported these findings qualitatively. A more robust quantitative analysis of the physiological data, presented similarly to the biomechanical metrics, would be a critical addition for future research to fully validate the system's dual--capability. Additionally, while the BLE 5.0 connection proved robust in our controlled setting, the potential for signal interference and data loss in more electromagnetically complex environments (e.g., a crowded stadium) remains a practical challenge for all real-time wireless sensing systems and warrants further investigation.

CONCLUSIONS

This research successfully demonstrated the design and effectiveness of a digital sports training system based on smart textiles. By providing athletes and coaches with real-time, quantitative, and multimodal data on biomechanics and physiology, the system proved to be a powerful tool for accelerating skill acquisition and optimizing physical performance. The controlled study showed that athletes using the smart textile system achieved significantly greater improvements in movement consistency and explosive power compared to those undergoing traditional training. This work contributes to the growing field of digital sports science by presenting an end-to-end system and providing strong scientific evidence of its efficacy, bridging the gap between laboratory-grade analysis and real-world athletic training. The potential for such technology to democratize elite-level coaching, personalize training programs, and reduce injury risk is immense, heralding a future where every athlete can train smarter and reach their full potential.

Availability of Data and Materials

The datasets used and/or analysed during the current study were available from the corresponding author on reasonable request.

Author Contributions

Wei Jin designed, collected and analyzed the data, and drafted the manuscript. Wei Jin conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Wei Jin participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Ethics Approval and Consent to Participate

This survey was conducted in compliance with Ethics Committee of Zhejiang Yuying College of Vocational Technology. Participants were informed of the study's purpose and data usage prior to participation, and responses were collected anonymously. No personally identifiable information was stored.

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Funding

Not applicable.

Conflict of Interest

The author declares no conflict of interest.

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