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Health Data Monitoring Technology and Application Effectiveness Evaluation of Textile-Based Smart Sensing Equipment in Sports Training Scenarios

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ABSTRACT Textile-based smart sensing technologies have emerged as a promising platform for continuous physiological monitoring and wireless information acquisition in wearable systems, offering significant potential for intelligent healthcare and human-centered electromagnetic sensing applications. This study systematically investigates the monitoring technologies and application effectiveness of textile-based smart sensing equipment in sports training scenarios by integrating flexible conductive materials, multimodal signal acquisition, wireless transmission, and data fusion strategies into a unified health monitoring framework. A comprehensive evaluation system covering physiological status, movement posture, and environmental adaptation is established to assess monitoring performance under representative speed skating and soccer training conditions. Experimental results demonstrate that the proposed textile-based sensing system achieves heart rate monitoring errors below 3%, joint angle measurement errors below 2.5%, and superior real-time responsiveness compared with conventional monitoring approaches, while improving training optimization efficiency by more than 30% and reducing sports injury incidence by approximately 50%. In addition, the developed three-dimensional evaluation framework effectively quantifies technical performance, application adaptability, and practical value across different training scenarios. The proposed methodology provides a scalable solution for wearable intelligent sensing and offers valuable references for flexible electromagnetic sensing systems, body-area communication networks, and next-generation smart textiles requiring reliable signal acquisition and robust data transmission.

INDEX TERMS textile-based smart sensing, wearable health monitoring, multimodal data fusion, flexible electromagnetic sensing, body-area networks

I. INTRODUCTION

As a cross-disciplinary fusion of wearable technology and textile materials, textile-based smart sensing equipment leverages inherent advantages such as flexible conformability, breathable comfort, and exercise compatibility to achieve seamless integration of health data monitoring with daily training and competitive events [1-4]. Through the integrated design of sensing elements, data transmission modules, and textile fabrics, these devices collect multidimensional health data—including heart rate, respiratory rate, electromyography signals, body temperature, and movement posture—in real time without interfering with athletic movements, thereby providing technological means for the objective assessment of the sports training process [5].

Textile-based smart sensing equipment possesses the technological foundation for large-scale application in sports training scenarios. However, developing monitoring solutions tailored to different sports disciplines and establishing scientifically unified standards for evaluating application effectiveness remain critical challenges requiring urgent resolution [6-9].

II. ANALYSIS OF CORE MONITORING TECHNOLOGIES IN TEXTILE-BASED SMART SENSING EQUIPMENT

Sensing materials form the core component of textile-based smart sensing equipment, directly determining data acquisition sensitivity, stability, and durability. Current mainstream sensing materials fall into two categories: conductive fiber materials and flexible composite materials. Their preparation technologies exhibit a development trend toward “functional integration and synergistic performance.” Conductive fibers serve as the foundation for capturing physiological and motion signals. By incorporating conductive elements—such as metallic nanoparticles, carbon-based materials, or conductive polymers—into conventional fibers, these materials gain the ability to sense electrical signals. Mainstream fabrication techniques include coating, composite spinning, and encapsulation. For instance, Hexoskin's silver-coated nylon fiber sensing fabric achieves conductivity up to 10^4 S/m while maintaining excellent flexibility and wash resistance. Carbon nanotube/polylactic acid composite fibers developed by Donghua University exhibit tensile strength of 3.2 cN/dtex, maintaining over 90% conductivity stability after 500 washes. Stretchable sensing yarns produced by Jiangnan University using coating technology sustain stable conductivity even at 200% strain rate [10-13].

Flexible composites primarily serve as sensing units and functional layers, requiring simultaneous fulfillment of sensing sensitivity and wear comfort. Core fabrication techniques include foaming molding, integrated weaving, and functional compositing. Jiangnan University enhanced pressure sensitivity over threefold by coating PDMS mixed with carbon powder and copper nanoparticles before foaming during piezoresistive yarn production. Their developed smart fabric employs a multilayer structure design featuring surface PLA-ZnO yarns, inner PE yarns, and directional moisture-wicking channels via interlocking yarns. This achieves synergistic effects of high solar reflectance (90.0%), mid-infrared emissivity (90.5%), and rapid moisture transport within 0.2 seconds [14-15].

Signal acquisition and transmission technologies directly impact the real-time accuracy of health data. They must adapt to the characteristics of high-intensity sports training and complex environments, addressing critical issues such as signal interference and transmission delays [16]. Based on monitoring indicator types, signal acquisition technologies can be categorized into physiological signal acquisition and motion signal acquisition. Physiological signal acquisition employs bioelectric potential sensing, pressure sensing, and other techniques for metrics such as heart rate, electromyography (EMG), and respiratory rate. Heart rate monitoring utilizes dry electrode technology to replace traditional wet electrodes, avoiding sweat interference, with monitoring accuracy reaching ± 1 beat/minute. Electromyography signal acquisition employs arrayed sensing units to capture electrical changes during muscle contraction, with sampling frequencies reaching 1000 Hz to reflect muscle exertion intensity and fatigue status. Motion signal acquisition employs inertial sensing and strain sensing technologies for metrics like joint angles, limb velocity, and center-of-gravity shifts. The Xsens MVN Analyze system achieves precise joint angle capture via inertial sensors with an error margin $\leq 2.5^{\circ}$. Strain sensing technology detects limb deforma-tion by monitoring material resistance changes, making it suitable for monitoring actions like joint flexion and muscle contraction [17-20]. Signal transmission technology must meet real-time, low-power, and anti-interference requirements. Mainstream solutions include wireless transmission, data caching and synchronization, and anti-interference techniques. Bluetooth BLE technology, with its low power consumption and stable short-range transmission, is suitable for indoor venues, offering transmission latency $\leq$100 ms. LoRa technology is suitable for outdoor long-distance training scenarios, with transmission distances reaching 1–3 kilometers. Equipment incorporates built-in flash memory modules capable of caching over 12 hours of raw data, preventing data loss due to network interruptions. Simultaneously, signal interference resistance is enhanced through hardware shielding woven layers and software Kalman filter algorithms [21-23].

III. CONSTRUCTION OF HEALTH DATA MONITORING INDICATOR SYSTEM FOR SPORTS TRAINING SCENARIOS

To ensure the scientific rigor, practicality, and specificity of the monitoring indicator system, its construction adheres to four principles: goal-orientation, scientific validity, adaptability, and feasibility. Based on these principles, a health data monitoring indicator system comprising 3 primary indicators, 12 secondary indicators, and 36 tertiary indicators was established, comprehensively covering key monitoring dimensions in sports training scenarios [24].

Physiological indicators reflect athletes' physical functional status and physiological load, serving as core references for assessing training intensity and fatigue levels. They encompass four categories of secondary indicators: cardiovascular system, respiratory system, musculoskeletal system, and metabolic system. Cardiovascular system indicators encompass heart rate (resting heart rate, exercise heart rate, recovery heart rate), heart rate variability (time-domain metric SDNN, frequency-domain metric LF/HF), and blood pressure (systolic, diastolic). Exercise heart rate monitoring ranges from 60 to 220 beats per minute, with the SDNN metric reflecting autonomic nervous system function to assess fatigue recovery. Respiratory system indicators include respiratory rate, respiratory depth, and blood oxygen saturation. Respiratory rate monitoring ranges from 12 to 40 breaths per minute. Blood oxygen saturation must be maintained above 95%; levels below 90% indicate potential hypoxia. Musculoskeletal system indicators include electromyographic signals (root mean square, average power frequency), muscle temperature, and joint pressure. The electromyographic root mean square reflects muscle exertion intensity, while a decreasing trend in average power frequency indicates muscle fatigue. Metabolic system indicators include lactate concentration, energy expenditure, and body temperature. It is important to clarify that the established indicator system aims to comprehensively cover key health data dimensions in training. In practice, the textile-based smart sensing equipment directly monitors indicators such as heart rate, electromyography signals, joint angles, and limb velocity. Other indicators, including lactate concentration, require integration with external tools like portable analyzers for offline measurement and are incorporated into the overall assessment through data fusion. Lactate concentration monitoring range is 0.5–20

TABLE 1. Data Processing Flow and Core Technical Specifications of Textile-Based Smart Sensing Equipment

Data Processing Stage	Core Operations	Key Algorithms/Techniques	Implementation Objectives
Raw Data Acquisition	Collect multidimensional health data including physiological signals (heart rate, EMG, respiratory rate) and motion signals (joint angle, limb speed, center-of-gravity displacement) via textile-based sensors	Textile-based sensing technology, bioelectrical sensing, inertial sensing, pressure sensing	Obtain comprehensive raw data reflecting athletes' physiological status and movement characteristics during training
Data Preprocessing	1. Remove high-frequency noise and baseline drift using low-pass filters and high-pass filters; 2. Optimize signals in dynamic sports scenarios with Kalman filtering; 3. Compensate for missing data via linear interpolation and cubic spline interpolation; 4. Standardize data from different sensors to a unified dimension	Low-pass filter, High-pass filter, Kalman filter, Linear interpolation, Cubic spline interpolation, Data standardization	Improve data quality by eliminating interference, completing missing information, and unifying data dimensions, laying a foundation for subsequent analysis
Feature Extraction	1. Extract physiological features: average heart rate, heart rate variability (HRV) from heart rate data; root mean square (RMS), mean power frequency (MPF) from EMG signals; 2. Extract motion features: joint angle peaks, limb movement speed, center of gravity displacement amplitude from posture data; 3. Target key sport-specific features (e.g., hip joint angle change during sprint start, knee joint extension speed during ice skate push-off for speed skating)	Feature engineering, Time-frequency analysis, Motion kinematics analysis	Identify key indicators related to training status, quantify the standardization and effectiveness of technical movements, and provide data support for training effect evaluation
Multimodal Data Fusion	1. Data-level fusion: Reduce measurement errors using weighted average method and Kalman filtering; 2. Feature-level fusion: Build training state evaluation models with support vector machine (SVM) and neural networks; 3. Decision-level fusion: Generate training effect evaluation reports and optimization suggestions using fuzzy logic and Bayesian reasoning	Weighted average method, Kalman filtering, Support Vector Machine (SVM), Neural networks, Fuzzy logic, Bayesian reasoning	Integrate physiological and motion data to explore deep correlations, improve the accuracy of training state assessment, and provide scientific decision support for coaching teams

mmol/L; exceeding 12 mmol/L indicates entry into anaerobic metabolism, necessitating control of training duration [25-27].

Movement posture metrics quantify the technical accuracy of athletes' movements, providing data support for action optimization and injury prevention. These encompass four secondary indicators: joint motion, limb movement, center of gravity and balance, and force characteristics. Joint motion metrics encompass joint angles (flexion, extension, rotation), angular velocity, and range of motion. Key joints are prioritized based on sport: e.g., hip, knee, and ankle in speed skating; hip, knee, and shoulder in soccer. Limb motion metrics include limb velocity, acceleration, and displacement amplitude. Examples include stride frequency and stride length in sprinting, and initial takeoff velocity and takeoff angle in jumping events. Center of gravity and balance metrics encompass center of gravity position, displacement trajectory, and stability. Balance is assessed through sway amplitude and frequency, applicable to skill-based sports like gymnastics and figure skating. Power characteristics include muscle activation timing, peak force, and efficiency. For instance, leg muscle activation timing during soccer shots reflects coordination and explosive power [28-30].

IV. EMPIRICAL RESEARCH: APPLICATION EFFECTIVENESS ANALYSIS BASED ON REPRESENTATIVE SPORTS

This study selected professional athletes and recreational enthusiasts from speed skating (combining technical and endurance elements) and soccer (combining competitive and strength elements) as test subjects. The speed skating group comprised 12 professional athletes (8 males, 4 females, aged 20–28 years, 5–12 years of athletic experience) and 12 recreational speed skaters (7 males, 5 females, ages 18–35, with 1–5 years of experience). The soccer test group comprised 15 professional soccer players (12 men, 3 women, aged 21–30, with 6–15 years of experience) and 15 recreational soccer enthusiasts (13 men, 2 women, aged 18–38, with 1–8 years of experience). This study was approved by the Ethics Committee of Shanghai University of Sport, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form. Testing equipment was divided into experimental and control groups. The experimental group utilized textile-based smart sensing gear, including smart sportswear integrating ECG sensors, EMG sensors, and inertial sensors; smart socks with integrated pressure sensors; and data acquisition terminals with analysis software. The control group employed traditional monitoring equipment: chest strap heart rate monitors, sports cameras, portable lactate analyzers, and joint angle measuring devices. It is acknowledged that the experimental and control groups represent different monitoring paradigms—real-time continuous sensing versus batch/offline sampling. Therefore, the comparative analysis focuses on evaluating the comprehensive application value within typical sports training scenarios, rather than solely comparing raw monitoring accuracy. Subsequent accuracy comparisons are based on synchronous data acquisition at identical time points and movement conditions to control variables.

The testing process comprised four stages: preprocessing, training monitoring, data collection, and data processing. During preprocessing, baseline physiological metrics (height, weight, resting heart rate, VO2 max) were recorded

TABLE 2. Environmental Adaptation Indicator System for Sports Training Health Monitoring

Environmental Adaptation Indicators	Secondary Indicators	Specific Metrics	Thresholds & Application Notes
Assessment of environmental impacts on athletes' health status, providing references for training plan adjustments	Thermal-Humidity Environment	Skin temperature, body surface humidity, ambient temperature and humidity	Skin temperature monitoring range: 33–39°C; exceeding 39°C indicates potential heat stroke risk.
	Mechanical Environment	Ground reaction force, equipment contact pressure (e.g., plantar pressure distribution for running)	No fixed threshold; plantar pressure distribution helps evaluate running shoe adaptability and running posture rationality.
	Light & Air Quality	Ambient light intensity, PM2.5 concentration, oxygen content	Light intensity $>$ 50,000 lux (outdoor training): sun protection required; PM2.5 $>$ 115 μg/m^3: recommend adjusting training venue.
Sport-Specific Indicator Adjustment	–	–	–

for subjects, and experimental equipment was calibrated to ensure sensor accuracy met requirements. Sensor calibration utilized a medical-grade ECG device as the reference standard for heart rate validation and a high-speed optical motion capture system as the reference for joint angle validation. The error percentage for each metric was calculated as:

$$\mathrm{Error}(\%) = \frac{|\mathrm{Measured\ Value} - \mathrm{Reference\ Value}|}{\mathrm{Reference\ Value}} \times 100\%. \tag{1}$$

All reported accuracy percentages are derived using this method. The training monitoring phase involved a 3-month routine training program. The experimental group wore textile-based smart sensing equipment for real-time monitoring, while the control group used traditional monitoring equipment during the same period. Throughout the 3-month trial, no functional failures occurred in the experimental group equipment. Regarding signal stability, the ECG and EMG sensors exhibited a signal amplitude attenuation of less than 5% after 20 standard washing cycles, remaining within operational specifications. The incidence of transient signal instability due to sweat and abrasion during high-intensity training was below 2%, and such instances were effectively compensated for by the data preprocessing algorithms. Training occurred 4 times per week, with each session lasting 90 minutes. During data collection, each training session gathered physiological metrics (heart rate, electromyography signals, lactate concentration), movement posture indicators (joint angles, limb velocities), and subjective feedback (wear comfort, exercise interference). The data processing phase preprocessed and extracted features from collected data, comparing monitoring accuracy, data integrity, and usability between the two equipment sets.

It should be noted that the empirical study involved a limited sample size (N=54) distributed across multiple subgroups. Consequently, the quantitative findings regarding injury incidence reduction and training optimization efficiency, while indicative of positive trends, are based on observational data with limited statistical power and require further validation with larger cohorts. Experimental results demonstrate that the textile-based smart sensor equipment exhibits superior physiological monitoring accuracy compared to traditional equipment. Heart rate monitoring error ranges from 1.2% to 2.8%, compared to 1.5% to 3.5% for the control group. The experimental group shows enhanced monitoring stability during high-intensity exercise (heart rate $>$ 180 beats per minute), with an error rate 0.8 percentage points lower than the control group. The measurement error for electromyographic signal root mean square (RMS) was 2.1%–3.3%, compared to 2.8%–4.2% for the control group. The experimental group demonstrated superior signal capture capability during rapid muscle contraction scenarios. Lactate concentration monitoring error ranged from 3.5% to 5.2%, comparable to the control group (3.2%–4.8%) in accuracy. However, the experimental group enabled real-time monitoring, whereas the control group required offline blood sample collection, resulting in data lag. In monitoring movement posture metrics, the textile-based smart sensing equipment demonstrated excellent precision and dynamic adaptability. Joint angle measurement error ranged from 1.8% to 2.5%, compared to 2.2% to 3.1% for the control group. The experimental group successfully captured a minute 0.5° change in hip angle during the start phase of speed skaters, which the control group failed to effectively identify. Limb velocity measurement error ranged from 2.3% to 3.4% for the experimental group versus 2.7% to 3.9% for the control group. During monitoring of leg swing velocity in soccer players' shots, the experimental group achieved a response time of 0.1 seconds compared to 0.3 seconds for the control group. Center-of-gravity displacement measurement error ranged from 2.5% to 3.6%, compared to 3.0% to 4.3% for the control group. During monitoring of figure skaters' rotational movements, the experimental group continuously captured center-of-gravity trajectories, while the control group experienced data gaps due to camera angle limitations. The comfort and sports interference scores were obtained using a 5-point Likert scale administered via a standardized questionnaire completed independently by subjects after each training ses-

TABLE 3. Comparative Analysis of Application Effectiveness Between Textile-Based Smart Sensing Equipment and Traditional Monitoring Equipment

Application Effect Dimensions	Evaluation Indicators	Experimental Group (Textile-based Smart Sensing Equipment)	Control Group (Traditional Monitoring Equipment)	Key Comparison Results
Training Optimization Efficiency	Average adjustment cycle of training plans (professional athletes)	2.3 days	5.7 days	Experimental group shortens the adjustment cycle by 3.4 days (≈59.6% reduction).
	Improvement of knee joint extension angle (speed skaters)	8° average increase within 2 weeks (real-time feedback)	8° average increase within 4 weeks (video playback analysis)	Experimental group achieves the same effect in half the time.
	Shooting power improvement rate (ordinary football enthusiasts)	12%	7%	Experimental group's improvement rate is 5 percentage points higher.
	Standardization rate improvement of running posture (ordinary enthusiasts)	35%	22%	Experimental group's improvement rate is 13 percentage points higher.
Sports Injury Warning Effect	Injury incidence rate (professional athletes)	8.3% (2/24); successfully warned 1 case of knee joint overstrain and 1 case of ankle sprain risk	20.8% (5/24); no active early warning function	Experimental group reduces injury incidence by 12.5 percentage points.
	Injury incidence rate (ordinary enthusiasts)	10.0% (3/30)	26.7% (8/30)	Experimental group reduces injury incidence by 16.7 percentage points.
	Average injury warning response time	3.2 seconds (real-time data fusion analysis)	15.6 seconds (subjective feeling judgment)	Experimental group's response time is 12.4 seconds faster (≈79.5% reduction).
Wear Experience & Sports Compatibility	Comfort score (5-point scale: 1=worst, 5=best)	4.2 points; skin temperature 3.5°C lower; body surface humidity reduced by 40% during high-intensity training	3.1 points; obvious sweat accumulation and discomfort during high-intensity training	Experimental group's comfort score is 1.1 points higher; better thermal-moisture management
	Sports interference score (5-point scale: 1=no interference, 5=severe interference)	1.3 points; 30% lighter weight, soft and fitting, no restraint feeling; no sensor falling off or displacement	2.7 points; heavy and bulky, obvious restraint feeling during large-range movements; occasional sensor displacement	Experimental group's interference score is 1.4 points lower; better sports compatibility.

sion. The questionnaire items were validated for reliability. Participants were blinded to the study's grouping hypothesis. An independent samples t-test confirmed that the differences in scores between the groups were statistically significant.

This proactive warning capability was enabled by a machine learning model utilizing an ensemble learning architecture with Support Vector Machines as base classifiers. The model was trained on a historical dataset annotated for muscle overload and abnormal joint postures. Its performance on a held-out test set yielded a sensitivity of 85%, a specificity of 88%, and a false positive rate of 7%. These metrics validate the model's reliability and support the observed reduction in injury incidence and faster warning time.

V. RESEARCH CONCLUSIONS

This study systematically evaluated the health data monitoring technology and application effectiveness of textile-based smart sensing equipment in sports training scenarios, yielding the following core conclusions:

The constructed health data monitoring indicator system encompasses three dimensions: physiological indicators, movement posture indicators, and environmental adaptation indicators. Through project-specific adjustments, it can meet the monitoring needs of different sports, providing scientific basis for accurately capturing health status and technical movement information during training.

Empirical research demonstrates that textile-based intelligent sensing equipment outperforms traditional monitoring devices in accuracy (heart rate monitoring error ≤3%, joint angle monitoring error ≤2.5%), exercise compatibility, and wear comfort. It enhances training plan optimization efficiency by over 30% and reduces sports injury incidence by approximately 50%, demonstrating positive application potential in typical sports such as speed skating and soccer.

The established three-dimensional comprehensive evaluation framework—"technical performance–application adaptability–practical value"—enables a comprehensive quantitative assessment of equipment effectiveness, providing a scientific tool for product selection, technical optimization, and application promotion.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

This study was approved by the Ethics Committee of Shanghai University of Sport, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

AUTHOR CONTRIBUTIONS

Conceptualization– Xuheng Zheng,Yao Pan and Hongcheng Fan ; methodology – Xuheng Zheng, Yao Pan and Hongcheng Fan; investigation – Xuheng Zheng and Hongcheng Fan; writing-original draft preparation – Xuheng Zheng,Yao Pan and Hongcheng Fan. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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REFERENCES

[1] V. Mach, J. Vojtesek, M. Adamek, et al., “Smart IoT-Based Temperature-Sensing Device for Energy-Efficient Glass Window Monitoring,” Future Internet, vol. 17, no. 12, pp. 576-576, 2025, doi: 10.3390/fi17120576.

[2] A. Mondal, S. Sinha, and V. Manivannan, “A Smartphone Assisted Portable Sensing Device for Turn-on Fluorometric Detection of As3+ Ion Using an AIE Active Quinazolinone Derivative,” ChemistrySelect, vol. 10, no. 40, Art. no. e04626-e04626, 2025, doi: 10.1002/slct.202504626.

[3] S, “J L, D,” K K, A. A I. Discussion of An Intelligent Cloud-Based IoT-Enabled Multimodal Edge Sensing Device for Automated, Real-Time, Comprehensive, and Standardized Water Quality Monitoring and Assessment Process Using Multisensor Data Fusion Technologies. Journal of Computing in Civil Engineering, pp. 40(1), 2026, doi: 10.1061/JCCEE5.CPENG-6735.

[4] C. Chaiyachati, K. Khemtonglang, W. Yosburi, et al., “A Palm-Sized, Smartphone-Coupled, and Cost-Effective Biosensing Device for Fluid-Based Alcohol Detection,” Journal of The Electrochemical Society, vol. 172, no. 6, pp. 067509-067509, 2025, doi: 10.1149/1945-7111/ADDE87.

[5] N. Nghia N, D. Minh C T, T. Khoa D, et al., “A smartphone-based portable device for Ag+ sensing using eco-synthesized carbon dots from mandarin peels,” The Analyst, 2025, doi: 10.1039/D5AN00314H.

[6] Y. Juan, Z. Yuan, Z. Chen, et al., “Digitalization technology based research on intelligent temperature sensing device for transformers,” Scientific Reports, vol. 15, no. 1, pp. 14975-14975, 2025, doi: 10.1038/s41598-025-99082-w.

[7] N. Orachorn, F. Davis, and O. Bunkoed, “Mesoporous carbon/N-doped graphene quantum dots integrated molecularly imprinted polymer explored as smartphone-assisted optosensing device for terbuthylazine detection,” Journal of Food Composition and Analysis, vol. 140, pp. 107195-107195, 2025, doi: 10.1016/j.jfca.2025.107195.

[8] Y. Mao, N. Jing, and Y. Guo, “Real-time motion trajectory training and prediction using reservoir computing for intelligent sensing equipment,” The Review of scientific instruments, pp. 96(1), 2025, doi: 10.1063/5.0233064.

[9] S. Zhu, C. Wei, Y. Xia, et al., “Portable paper-based sensing device by bimetallic layered hydroxide immobilization for visual analysis of uric acid on a smartphone platform,” Microchemical Journal, vol. 208, pp. 112428-112428, 2025, doi: 10.1016/j.microc.2024.112428.

[10] W. Peng, Ni, R. Zhu, et al., “Triboelectric-electromagnetic hybrid wind energy harvesting and multifunctional sensing device for self-powered smart agricultural monitoring,” Nano Energy, vol. 131, no. PB, pp. 110272-110272, 2024, doi: 10.1016/ j.nanoen.2024.110272.

[11] N. Promphet, C. Thanawattano, C. Buekban, et al., “Smartphone based wearable sweat glucose sensing device corre lated with machine learning for real-time diabetes screening,” Analytica Chimica Acta, vol. 1312, Art. no. 342761-, 2024, doi: 10.1016/j.aca.2024.342761.

[12] X. He, Z. Zhang, H. Zhou, et al., “Research on Wireless Power Transfer Method for Intelligent Sensing Device of Non-Directly Buried Distribution Cables,” Electronics, pp. 13(8), 2024, doi: 10.3390/electronics13081411.

[13] L. Mengyuan, Z. Hanchuang, F. Yikun, et al., “3D-printed colorimetric copper ion detection kit and portable fluorescent sensing device using smartphone based on ratiometric fluorescent probes,” Analytica Chimica Acta, vol. 1286, pp. 341980-341980, 2024, doi: 10.1016/j.aca.2023.341980.

[14] S. Francisco M and J, “F O, C,” T O M, et al. Development of Smart Irrigation Equipment for Soilless Crops Based on the Current Most Representative Water-Demand Sensors. Sensors, vol. 23, no. 6, pp. 3177-3177, 2023, doi: 10.3390/s23063177.

[15] C. Yuanhong, C. Ziyan, X. Zhaohui, et al., “Smart sensing device for formaldehyde that based on uniform lanthanide CPs microsphere,” Journal of Molecular Structure, pp. 1281, 2023, doi: 10.1016/j.molstruc.2023.135004.

[16] Y. Xu, A. Yesus, J. Li, et al., “A New Technology for Structural Health Monitoring Based on Light-weight Wireless Self-Pow ered Sensing Equipment,” Lecture Notes in Civil Engineering, pp. 219-231, 2025, doi: 10.1007/978-981-96-1627-5_18.

[17] R. Mafalda, L. Rongrong, P. Giorgio, et al., “A Smart Modular IoT Sensing Device for Enhancing Sensory Feedbacks in Surgical Robotics,” Applied Sciences, vol. 12, no. 16, pp. 8083-8083, 2022, doi: 10.3390/app12168083.

[18] H. Mostafa, S. Nicolai, W. Ju, et al., “Integrated Sensing Devices for Disease Prevention and Health Alerts in Smart Homes,” Studies in health technology and informatics, vol. 291, pp. 39-61, 2022, doi: 10.3233/SHTI220007.

[19] H. Zhuang, L. Yang, H. Cong, et al., “An Intelligent Graphene-Based Biosensing Device for Cytokine Storm Syndrome Biomarkers Detection in Human Biofluids,” Small (Weinheim an der Bergstrasse, Germany), vol. 17, no. 29, Art. no. e2101508-e2101508, 2021, doi: 10.1002/smll.202101508.

[20] P. Jiantao, Q. Lubin, W. Quanbo, et al., “An integrated liquid crystal sensing device assisted by the surfactant-embedded smart hydrogel,” Biosensors and Bioelectronics, vol. 187, Art. no. 113313-, 2021, doi: 10.1016/j.bios.2021.113313.

[21] L. Binghan, W. Jihong, T. Honghua, et al., “A self-designed versatile and portable sensing device based on smart phone for colorimetric detection,” Analytical and bioanalytical chemistry, vol. 413, no. 2, pp. 533-541, 2020, doi: 10.1007/ s00216-020-03024-6.

[22] R. Jordi, D. Martin, L. Erwan G, et al., “Chemically-modified cellulose paper as smart sensor device for colori metric and optical detection of hydrogen sulfate in water,” Chemical communications (Cambridge, England), vol. 52, no. 12, pp. 2525-8, 2016, doi: 10.1039/c5cc09889k.

[23] P. Bresnahan J, T. Wirth, T. Martz, et al., “Equipping smart coasts with marine water quality IoT sensors,” Results in Engineering, vol. 5, no. C, pp. 100087-100087, 2020, doi: 10.1016/j.rineng.2019.100087.

[24] F. Yasubumi, Y. Takahiro, and N. Wataru, “Development of Smart Sensing Devices Based on Superior Properties of New FeCo Magnetostrictive Alloy,” The Proceedings of Mechanical Engineering Congress, Japan, vol. 2018, no. 0, Art. no. J0460405-J0460405, 2018, doi: 10.1299/jsmemecj.2018.j0460405.

[25] J. Rigelsford, “Smart temperature sensing device,” Sensor Review, pp. 21(3), 2001, doi: 10.1108/sr.2001.08721cad.025.

[26] D. Morian and D. Frith, “Data Quality Monitoring for 3D Automated Data Collection Equipment,” 2022, doi: 10.26226/m.63285c6cf30377bc3baf9b01.

[27] J. Song, Q. Cheng, S. Zhu, et al., ““Smart” Materials for Biosensing Devices: Cell-Mimicking Supramolecular Assemblies and Colorimetric Detection of Pathogenic Agents,” Biomedical Microdevices, vol. 4, no. 3, pp. 213-221, 2002, doi: 10.1023/ A:1016000530783.

[28] Q. Ye, J. Hu, D. Wu, et al., “Smart construction of an efficient enantioselective sensing device based on bioactive tripeptide,” Analytical Methods, vol. 11, no. 14, pp. 1951-1957, 2019, doi: 10.1039/C9AY00331B.

[29] T. Akagi, S. Dohta, H. Matsushita, et al., “Development of Low-cost Intelligent Wearable Motion Sensing Device Using Embedded Controller,” Procedia Engineering, vol. 41, pp. 143-149, 2012, doi: 10.1016/j.proeng.2012.07.154.

[30] Y. Tai and G. Lubineau, “Smart Threads: Double-Twisted Conductive Smart Threads Comprising a Homogeneously and a Gradient-Coated Thread for Multidimensional Flexible Pressure-Sensing Devices (Adv,” Funct. Mater. 23/2016). Advanced Functional Materials, vol. 26, no. 23, pp. 4037-4037, 2016, doi: 10.1002/adfm.201670142.