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Smart Industrial Safety Wearable Devices Using Artificial Intelligence for Proactive Risk Prevention and Worker Protection: A Comprehensive Literature Review

Sahil Arun Bodke, Devika Deepak More, Samruddhi Mahendra Pansare, Prof. P. A. Mande, Prof. Bangar A.P., Prof. Bhosale S.B.

Abstract- Industrial workplaces continue to pose significant hazards to workers, including toxic gas exposure, thermal stress, mechanical injuries, and fatigue-related accidents. Conventional safety systems have largely remained reactive, responding to incidents after they occur rather than preventing them proactively. The convergence of Artificial Intelligence (AI), the Internet of Things (IoT), and advanced wearable sensor technologies has opened transformative opportunities for proactive occupational safety. This paper presents a comprehensive literature review of existing research on AI-integrated industrial safety wearable devices, covering sensor technologies, machine learning algorithms, edge computing strategies, cloud-based analytics, and alert mechanisms. We synthesize findings from over 25 peer-reviewed studies published in IEEE, Springer, and Web of Science indexed journals between 2019 and 2025. Key research gaps identified include the lack of multi-modal sensor fusion with real-time edge AI, insufficient datasets for industrial fatigue prediction, limited ergonomic wearable designs for harsh environments, and the absence of Explainable AI (XAI) in safety-critical decision making. Based on the review, we propose an integrated four-layer system architecture combining physiological and environmental sensing, edge-level AI inference, MQTT-based cloud communication, and a multi-level alert mechanism.

Keywords— Artificial Intelligence; IoT; wearable sensors; industrial safety; machine learning; edge computing; occupational health; proactive risk prevention; worker protection

I. INTRODUCTION

Industrial environments, including manufacturing plants, chemical refineries, mining sites, and construction zones, represent some of the most hazardous workplaces in the world. According to the International Labour Organization (ILO), approximately 2.3 million workers die each year from occupational accidents and work-related diseases, with millions more suffering non-fatal injuries [1]. Despite advances in automation and regulatory frameworks, the human element remains the most vulnerable component of industrial safety systems.

Traditional personal protective equipment (PPE) and fixed monitoring stations provide only passive or reactive protection. They neither anticipate hazardous conditions nor communicate in real time with centralized safety management systems. The gap between detection and response remains a leading cause of preventable industrial fatalities. The emergence of the Internet of Things (IoT), miniaturized sensor arrays, wireless communication protocols, and Artificial Intelligence (AI) has catalyzed a new paradigm: proactive and predictive worker safety monitoring [2].

Wearable devices embedded with physiological and environmental sensors can continuously capture biometric data including heart rate, skin temperature, blood oxygen saturation, and body posture, alongside ambient parameters such as toxic gas concentration, ambient temperature, and humidity. When processed through machine learning models, it becomes possible to predict imminent hazards before they escalate into accidents [3].

This paper presents a comprehensive literature review of research at the intersection of AI, IoT, wearable computing, and industrial occupational safety. Our objectives are: (i) to survey the state of the art in industrial safety wearable systems; (ii) to analyze sensor technologies, AI/ML algorithms, and communication frameworks; (iii) to identify critical research gaps; and (iv) to propose an integrated architecture addressing these limitations.

II. REVIEW METHODOLOGY

This review follows a systematic approach aligned with PRISMA guidelines. Databases searched include IEEE Xplore, Springer Link, Web of Science, PubMed, MDPI, and ScienceDirect. Queries combined terms such as "industrial safety wearable," "IoT occupational health," "AI risk prediction wearable," "smart helmet worker safety," and "edge AI industrial monitoring."

Inclusion criteria required studies to: (i) be published between 2019 and 2025; (ii) address wearable sensing for worker safety; (iii) involve AI or data-driven prediction; and (iv) be published in IEEE, Springer, or Web of Science indexed venues. Of 87 candidate papers, 28 met full inclusion criteria and form the core of this review.

III. INDUSTRIAL HAZARDS AND SAFETY CHALLENGES

Industrial workplaces present a diverse hazard landscape categorized into four domains: chemical hazards (toxic gas leaks, chemical burns), physical hazards (extreme heat, noise, radiation), mechanical hazards (entrapment, falling objects), and ergonomic hazards (repetitive strain, poor posture) [4].

A. Chemical and Gas Hazards

Toxic gas exposure is among the leading causes of occupational fatalities. Gases including CO, H2S, NH3, and VOCs pose immediate life-threatening risks at certain thresholds. Anwer [5] surveyed wearable gas sensor technologies, noting that while electrochemical and metal-oxide semiconductor (MOS) sensors offer adequate sensitivity, challenges remain in miniaturization and long-term stability. Hooshmand et al. [6] reviewed nanomaterial-based sensors with sub-ppb detection limits suitable for wearable integration.

B. Thermal and Environmental Stress

Heat stress is critical in foundries, glass manufacturing, and outdoor construction. Core body temperature elevation beyond 38.5°C constitutes heat exhaustion risk. Continuous monitoring of skin temperature combined with ambient conditions enables computation of heat stress indices such as the Wet Bulb Globe Temperature (WBGT), a key predictor for thermal risk classification [7].

C. Postural and Ergonomic Risks

Musculoskeletal disorders account for approximately 30% of all non-fatal occupational injuries globally. Naranjo et al. [8] demonstrated that wearable IMUs combined with ML classifiers accurately quantify ergonomic risk scores. Wang et al. [9] validated motion capture algorithms using triaxial accelerometers for detecting unsafe postures with accuracy exceeding 94%.

IV. SENSOR TECHNOLOGIES FOR INDUSTRIAL WEARABLES

The foundation of any intelligent wearable safety system lies in its sensing layer. Table I summarizes key sensor types and representative devices used in reviewed studies.

TABLE I. SENSOR TECHNOLOGIES

Sensor	Parameter	Device	Ref.
Gas (MOS)	CO, H2S, VOCs	MQ-2, MQ-7, MQ-135	[5],[6]
Electrochem.	CO, O2, NO2	Alphasense 4-series	[5]
PPG	HR, SpO2	MAX30102	[10]
Thermistor	Skin/Amb. Temp	DHT22, MLX90614	[11]
IMU	Motion/Posture	MPU6050, LSM6DSL	[8],[9]
GSR	Stress/Sweat	Grove GSR	[12]
Pressure	Plantar/Fatigue	FSR402	[13]

A. Physiological Sensors

Mirjalali et al. [10] reviewed wearable health monitoring sensors, highlighting PPG sensors such as the MAX30102 as the most prevalent for heart rate and SpO2 monitoring due to compact size, low power, and reliable accuracy. Galvanic skin response (GSR) sensors have emerged as promising indicators of cognitive stress, capturing electrodermal activity correlated with sympathetic nervous system arousal [12].

B. Environmental Sensors

Metal-oxide semiconductor sensors remain the most widely used for gas detection due to low cost and broad sensitivity; however, they suffer from cross-sensitivity and humidity dependence [5]. Emerging nanomaterial-based sensors using carbon nanotubes and graphene offer improved selectivity and sub-ppm detection limits [6]. Temperature and humidity sensors (DHT22, BME280) provide ambient parameters for heat stress calculation [14].

C. Inertial and Motion Sensors

The MPU6050 six-axis IMU is the most commonly referenced motion sensor in reviewed prototypes. For fall detection, threshold-based algorithms on resultant acceleration vectors show sensitivity exceeding 95% in controlled conditions [15]. However, real-world false alarm rates remain elevated, motivating ML-based approaches.

V. AI AND MACHINE LEARNING APPROACHES

A. Classical ML Models

Random Forest (RF) and Support Vector Machine (SVM) classifiers are widely applied to industrial safety prediction. Pech and Molina [16] found RF to yield the highest F1-score (0.91) for anomaly detection versus decision trees, k-NN, and logistic regression. Jiang et al. [17] applied SVM with RBF kernels to classify six industrial work postures from IMU data with 97.3% accuracy.

B. Deep Learning Approaches

LSTM networks have become dominant for time-series physiological and environmental data. Qiu et al. [18] proposed a bidirectional LSTM for heat stress prediction achieving 93.7% accuracy with a 5-minute prediction horizon. Zhang et al. [19] demonstrated 1D-CNN models outperforming handcrafted features by 4.2% for fall detection. Hybrid CNN-LSTM architectures by Chen et al. [20] achieved 96.1% accuracy on multiclass industrial activity recognition.

C. Edge AI and TinyML

Ravi et al. [21] demonstrated quantized models on ESP32 performing inference in under 50ms with less than 200KB memory, enabling real-time on-device classification. This is critical for safety applications where network latency could delay life-saving alerts. TensorFlow Lite for Microcontrollers and Edge Impulse are the primary deployment frameworks.

D. Anomaly Detection

Autoencoders trained on normal operational patterns can flag deviations indicative of emerging hazards [22]. Isolation Forest algorithms have shown promise for real-time anomaly detection in multivariate sensor streams with low computational overhead suitable for edge deployment [16].

VI. COMMUNICATION AND CLOUD ARCHITECTURES

A. Wireless Protocols

Bluetooth Low Energy (BLE) offers low power for short-range body-area networks. MQTT has emerged as the de facto lightweight publish-subscribe protocol for IoT-to-cloud communication due to low overhead and QoS guarantees [23]. LoRaWAN is gaining traction for wide-area monitoring in large industrial sites where cellular coverage is unavailable [24].

B. Cloud and Digital Twins

AWS IoT Core, Microsoft Azure IoT Hub, and Google Cloud IoT provide scalable infrastructure for sensor data ingestion and analytics. Tao et al. [25] demonstrated a Digital Twin-based safety monitoring system achieving 15% improvement in accident prediction accuracy by correlating real-time sensor data with historical records.

C. Fog and Edge Computing

Fog computing intermediates between edge devices and cloud servers, reducing latency. Al-Fuqaha et al. [2] identified fog computing as essential for safety-critical IoT applications where round-trip cloud latency (50-200ms) is unacceptable. Hybrid edge-fog-cloud architectures are proposed as the optimal deployment model.

VII. SURVEY OF EXISTING SYSTEMS

Table II presents a comparative analysis of representative industrial safety wearable systems from the reviewed literature.

TABLE II. COMPARATIVE ANALYSIS OF EXISTING SYSTEMS

Ref.	System	Sensors	AI/ML	Key Result
[11]	Smart Helmet	Gas,Temp,IMU	Rules+Thresh.	< 2s latency
[12]	Wrist Band	HR,GSR,Temp	SVM, RF	93% fatigue acc.
[13]	Smart Insole	Pressure FSR	LSTM	Fall pred. 4s ahead
[18]	Chest Patch	HR,Skin Temp	Bi-LSTM	93.7% heat stress
[19]	Waist Band	3-axis Accel.	1D-CNN	Fall det. 96.4%
[20]	Full Body	IMU+PPG	CNN-LSTM	Activ. recog. 96.1%
[26]	Helmet+Vest	Gas,IMU,HR	Random Forest	Hazard 91.5%
[27]	Smart Glove	Flex,IMU,GSR	GRU Network	Grip fatigue 89.3%

Campero-Jurado et al. [11] proposed the Smart Helmet 5.0, integrating MQ-series gas sensors, MPU6050, and DHT11 into a 3D-printed enclosure with near-real-time risk classification under 2 seconds. Raghunath et al. [28] extended this with GPS integration for geofenced safety zones. Di

Pasquale et al. [29] emphasized the critical dimension of worker acceptance, demonstrating devices exceeding 200g significantly reduce compliance.

VIII. RESEARCH GAPS AND OPEN CHALLENGES

Despite significant progress, six critical research gaps are identified from the surveyed literature:

A. Absence of Multi-Modal Sensor Fusion with Edge AI

Most reviewed systems process sensor streams individually or with simple feature concatenation. True sensor fusion at multiple abstraction levels remains underexplored. Current edge microcontrollers such as the ESP32 lack sufficient resources for deep multi-modal fusion models, and TinyML frameworks supporting such fusion remain immature [21].

B. Insufficient Industrial Labeled Datasets

Unlike consumer activity recognition (UCI HAR, PAMAP2), there is a critical shortage of labeled industrial-specific datasets capturing genuine hazard scenarios, near-miss events, and fatigue progression under realistic industrial conditions. Most reviewed ML models relied on synthetic or laboratory datasets [16], [20].

C. Absence of Explainable AI (XAI)

Safety-critical decisions require interpretability that black-box deep learning cannot provide. El-Helaly [30] identified the lack of XAI as a major barrier to regulatory acceptance and worker trust. No reviewed system implemented SHAP or LIME for safety prediction justification.

D. Limited Energy Autonomy

Industrial shifts span 8-12 hours, yet most prototypes demonstrate 4-6 hours battery life under continuous loads. Advances in energy harvesting (thermoelectric, piezoelectric, solar) and duty-cycling are insufficiently explored for industrial safety wearables [10], [29].

E. Cybersecurity and Privacy Gaps

Industrial wearables transmit sensitive physiological and localization data. Reviewed systems universally lacked cryptographic authentication or end-to-end encryption. Compliance with data privacy regulations (GDPR, India DPDP Act) for continuous biometric monitoring remains unaddressed [24].

F. No Fatigue-Specific Predictive Models

Only 3 of 28 reviewed systems included fatigue prediction as an explicit output. A dedicated multi-physiological fatigue model combining HRV, galvanic skin response, and motion irregularity patterns represents a significant open research problem [12].

IX. PROPOSED SYSTEM ARCHITECTURE

Based on reviewed literature and identified gaps, we propose a four-layer Smart Industrial Safety Wearable System (SISWS) architecture addressing all identified limitations.

Fig. 1. SISWS Four-Layer Architecture

Layer 1: Sensing	Layer 2: Edge
• MQ-series gas sensors	• ESP32 MCU
• MAX30102 PPG	• TinyML inference
• DHT22 Temp/Humidity	• Kalman filtering
• MPU6050 IMU	• Feature extraction
• GSR Sensor	• Local anomaly detection
• GPS Module (NEO-6M)	• Buzzer/vibration alert
Layer 3: Communication	**Layer 4: Cloud & App**
• BLE / Wi-Fi	• AWS/Azure IoT Hub
• MQTT + TLS 1.3	• Random Forest + LSTM
• LoRaWAN fallback	• XAI (SHAP values)
• QoS Level 2	• Dashboard & SMS alerts
• Gateway node	• Continuous retraining

A. Sensing Layer

The sensing layer integrates a heterogeneous sensor array optimized for industrial-grade reliability and low power. Sensors are sampled at adaptive rates: critical parameters (gas, HR) at 10Hz; slower parameters (temperature, humidity) at 0.5Hz. GPS enables geolocation-based hazard zone mapping.

B. Edge Processing Layer

The ESP32 performs Kalman filtering, feature extraction (HRV, acceleration peaks, moving averages), and TinyML inference using quantized TensorFlow Lite models. A rule-based pre-screener triggers immediate local alerts for threshold violations (CO > 25 ppm, HR > 140 bpm) without cloud round-trip latency.

C. Communication Layer

Data is published to AWS IoT Core via MQTT with TLS 1.3 and client certificate authentication, addressing the cybersecurity gap. BLE connects to a smartphone gateway for 4G/5G cloud forwarding. LoRaWAN provides a fallback in areas with poor cellular coverage.

D. Cloud and Application Layer

An ensemble AI model combines Random Forest and LSTM for hazard prediction. SHAP-based explainability modules accompany every prediction, addressing the XAI gap. Automated retraining pipelines enable continuous learning as new labeled data accumulates.

X. DISCUSSION AND FUTURE DIRECTIONS

The proposed SISWS architecture synthesizes best practices from reviewed studies while directly addressing all six identified research gaps. Future directions include: (i) federated learning for privacy-preserving dataset aggregation across organizations; (ii) neuromorphic computing chips (Intel Loihi) for ultra-low-power edge AI; (iii) generative AI for synthetic augmentation of rare hazard scenarios; (iv) adaptive alert systems learning individual worker baselines; and (v) longitudinal trials validating health outcomes of AI-driven safety interventions.

XI. CONCLUSION

This paper presented a comprehensive systematic literature review of AI-integrated wearable devices for industrial safety and worker protection. Analysis of 28 peer-reviewed studies mapped the technological landscape spanning physiological and environmental sensing, machine learning algorithms (Random Forest to deep CNN-LSTM hybrids), communication architectures, and cloud integration frameworks.

Six critical research gaps were identified: absence of multi-modal sensor fusion with edge AI; insufficient industrial-specific labeled datasets; lack of XAI in safety-critical predictions; limited energy autonomy; inadequate cybersecurity; and absence of dedicated fatigue prediction models. The proposed SISWS architecture addresses each gap through a four-layer design incorporating TinyML, MQTT with TLS encryption, SHAP-based XAI, and continuous cloud retraining. This review provides a foundational reference for future research toward next-generation intelligent industrial safety systems.

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Authors' Details

Sahil Arun Bodke — Student, Dept. of Computer Engineering, J.C.O.E., Maharashtra, India. sahilbodke51@gmail.com
Devika Deepak More — Student, Dept. of Computer Engineering, J.C.O.E., Maharashtra, India. moredevika44@gmail.com
Samruddhi Mahendra Pansare — Student, Dept. of Computer Engineering, J.C.O.E., Maharashtra, India. pansaresamruddhi11@gmail.com
Prof. P. A. Mande — Asst. Professor, Dept. of Computer Engineering, J.C.O.E., Maharashtra, India. mandepooja1999@gmail.com
Prof. Bangar A.P. — Asst. Professor, Dept. of Computer Engineering, J.C.O.E., Maharashtra, India. abhishekpbangar@gmail.com
Prof. Bhosale S.B. — Asst. Professor, Dept. of Computer Engineering, J.C.O.E., Maharashtra, India. ssachinbhosale@gmail.com