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IoT-Based Industrial Worker Safety Monitoring System Using Wi-Fi Zone Detection, Wearable Health Monitoring, and Fall Detection

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ABSTRACT—

Much of a plant floor, and every basement or tunnel, has no GPS fix, and one supervisor cannot watch every worker at once. We describe a wearable Internet of Things (IoT) prototype for these places. One small node estimates the worker's zone from the signal strength of nearby Wi-Fi access points, reads heart rate and blood-oxygen saturation with an optical sensor, and checks an inertial sensor for possible falls. A supervisor follows it all on a live control-room dashboard. The node is built on a Saeed Studio XIAO ESP32-S3 and posts readings to a Node.js/Express backend, which forwards events to a React dashboard through Socket.IO. Zones are derived from the received signal strength indicator (RSSI) of registered access points, and falls are flagged when a high acceleration magnitude is followed by inactivity. The paper also reviews related work on wearable industrial safety, RSSI localization and threshold-based fall detection, writes the zone and fall rules down formally, and sets out a repeatable protocol for measuring zone accuracy, fall precision and recall, sensor agreement, delivery rate and alert latency. The dashboard is implemented, and screenshots taken with simulated workers are included. No measured results are given here; they will follow once the protocol has been run. This is a research prototype, not a certified industrial safety product or a clinically validated medical device.

Index Terms—Internet of Things, industrial worker safety, wearable sensors, ESP32-S3, Wi-Fi RSSI, indoor zone estimation, fall detection, heart-rate monitoring, real-time monitoring.

I. INTRODUCTION

Accidents and illness at work take a heavy toll on workers and on the economy. Wearable devices arrived with Industry 4.0 as one way to keep watch over safety on site [1]. Yet most plants still run on supervisor rounds, head-counts and radio check-ins. A round only shows a supervisor who is where at that moment, and a radio check-in works only if the worker is able to speak up.

Two things get in the way. Indoors, and especially underground, satellite positioning mostly fails, so the system has to work out location from some other signal; [1] surveys the localization and communication options used in wearable safety products. The hazards also arrive together. A worker can wander into a restricted zone, collapse, or show unusual vital signs, and these are normally watched by separate tools. Wearables for miners, including a wearable safety management concept, have been studied in the mining sector [2]. Earlier occupational-safety work had already suggested that wireless wearable sensors could combine environmental, physiological and location data into one picture [3].

The prototype described here is deliberately cheap. It reuses Wi-Fi that is often already in the building to get a rough zone, and it places heart-rate, SpO2 and fall sensing on one microcontroller. Our question is simple: can an inexpensive wearable and the existing access points (APs) give a

supervisor zone-level visibility, vital signs with quality flags and prompt fall alerts? A second question follows from the first, namely how a prototype of this kind should be tested.

Contributions. The paper offers four things: (i) an end-to-end architecture from the wearable sensors to an administrator dashboard; (ii) a formal RSSI-based zone estimation rule with a calibration procedure; (iii) a threshold-based fall pipeline with an explicit inactivity check; and (iv) a repeatable evaluation protocol with defined metrics. The working dashboard is shown as well. This is a design and methods paper and makes no performance claim.

II. RELATED WORK

A. Wearable and IoT Worker Monitoring

A survey of industrial wearables divides them into monitoring, supporting, training and tracking roles, then goes through data metrics, communication technologies, localization techniques and open problems [1]. For mining, one review of wearable devices puts forward a wearable safety management system for miners [2]. The NIOSH technology review looks at smart wearable sensors, wireless sensor networks and low-power embedded computing, and mentions person-down detection and ultra-wideband (UWB) tracking among the uses [3]. Another systematic review, on wireless sensor networks in underground mines, files the literature under location tracking, physiological and body-kinematics monitoring, and environmental monitoring [4]. More recently, a 2024 mine IoT system combined a Bluetooth bracelet for vital signs with a miner's lamp that detects several gases and tracks position, relying on 5G and UWB base stations; its authors report a positioning deviation under 0.3 m and latency of at most 20 ms [5]. Such a system needs purpose-built positioning and cellular equipment. Our prototype instead settles for coarse zones using APs that may already be installed.

B. Wi-Fi RSSI Localization and Zone Estimation

Wi-Fi RSSI fingerprinting is a well-studied topic. One overview of machine-learning schemes covers preprocessing, data augmentation, prediction models and post-processing [6]. The trouble is that RSSI moves around with interference and instability, most of all in places that keep changing, and fingerprint matching suffers; a recent systematic review examines radio-map construction and machine-learning fixes for this [7]. Building the fingerprint database also takes a great deal of effort, which is why crowdsourced site surveys were proposed [8]. These findings shaped our design. Full fingerprinting is expensive and brittle, so the prototype decides only at zone level and counts RSSI uncertainty as a key limitation (Section IX).

C. Wearable Fall Detection

Bourke et al. tried threshold-based detection with trunk-mounted tri-axial accelerometers, using simulated falls and activities of daily living (ADL). In their data a single threshold on resultant acceleration separated falls from ADL [9]. A wide-ranging review of fall detection systems names the problems still open: real-life performance, usability, user acceptance, power use, real-time operation, sensing limits, privacy and the lack of recorded real falls [10]. Because of this, results from simulated falls should not be taken to hold in the field.

D. Optical Heart-Rate and SpO2 Sensing

Photoplethysmography (PPG) is a low-cost optical technique that detects blood-volume changes in the microvascular bed. Its waveform has a pulsatile (AC) part on top of a slowly changing (DC) baseline [11]. The MAX30102 is a reflective pulse-oximeter and heart-rate module built from LEDs and a photodetector, with programmable sample rate and LED current [12].

E. Research Gap

Taken together, the studies above tend to treat localization, physiological sensing or fall detection one at a time, depend on heavy infrastructure, or are reviews. Among the sources we examined, none documents a low-cost, zone-level prototype that reuses existing Wi-Fi, covers all three layers and comes with an explicit evaluation protocol. This applies only to what we read; a wider systematic search is needed before anyone can claim novelty.

III. PROBLEM STATEMENT AND OBJECTIVES

The goal is to give a supervisor near-real-time awareness of each worker where GPS does not work and manual observation is limited. The prototype must satisfy these requirements:

- R1, zone estimation without GPS: infer a worker's zone from Wi-Fi AP identifiers and RSSI.
- R2, sensor collection: obtain heart-rate and SpO2 estimates along with signal-quality flags.
- R3, local fall detection: detect a possible fall on the wearable itself, regardless of network state.
- R4, real-time delivery: push status and alerts to a dashboard with bounded delay.
- R5, liveness: flag offline devices and stale telemetry.
- R6, persistence: keep a history of incidents.

The work is organised around four research questions. RQ1: how accurately does the strongest-registered-AP rule assign zones, and how stable is it as RSSI fluctuates? RQ2: what sensitivity and precision can the threshold fall detector reach on a labelled, safely simulated test set? RQ3: how well do heart-rate and SpO2 estimates agree with reference instruments? RQ4: what are the telemetry delivery rate, end-to-end alert latency and offline-detection time?

IV. PROPOSED SYSTEM ARCHITECTURE

Fig. 1 gives the intended architecture and Fig. 2 the message flow. Readings pass from the sensors to the ESP32-S3, then over Wi-Fi to the Node.js/Express backend, through storage and alert handling, and finally by Socket.IO to the React administrator dashboard.

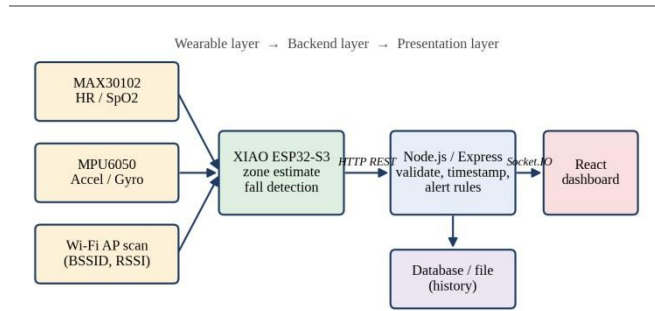


Fig. 1. Intended system architecture. The database layer may be a relational store or a local file.

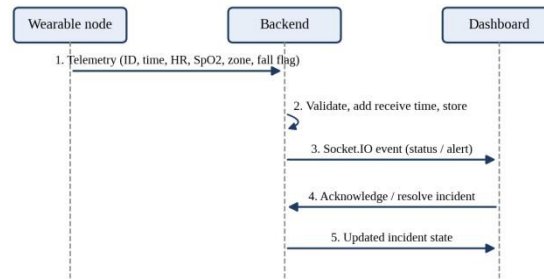


Fig. 2. Data-flow sequence between node, backend and dashboard.

A. Subsystems

- 1) Wearable hardware. The node is a Seeed Studio XIAO ESP32-S3 [13] carrying a MAX30102 pulse-oximeter and heart-rate sensor [12] and an MPU6050 accelerometer and gyroscope for fall detection [14], powered by a rechargeable battery and power-management circuitry.
- 2) Sensor acquisition. The firmware samples the MAX30102 (red and infrared optical signals) and the MPU6050 (acceleration and angular rate), and attaches signal-quality flags to the heart-rate and SpO2 estimates.
- 3) AP scanning. The ESP32-S3 scans for nearby APs and records the BSSID and RSSI of each. It works on 2.4 GHz IEEE 802.11 b/g/n [13], so an AP that broadcasts only on another band cannot be seen, and AP planning must allow for this.
- 4) Zone estimation and fall detection. The rules of Section V are applied to the AP scan results and the inertial data. Fall detection runs on the node itself, so that it does not depend on the network (R3). The zone label is derived from the AP list as in Section V-A, either on the node or on the backend.
- 5) Telemetry. The node sends each reading as a JSON message over HTTP REST on its Wi-Fi link to the backend.
- 6) Backend and storage. The Node.js/Express backend validates and timestamps each message, applies the alert rules, and stores the data and the incident history.
- 7) Real-time delivery and dashboard. Socket.IO pushes events from the backend to the React administrator dashboard, which shows each worker's zone, vital signs, link status and open incidents. An administrator can acknowledge and resolve incidents there.

Table I sets the reviewed approaches beside the proposed prototype.

TABLE I. Comparison of Reviewed Approaches with the Proposed Prototype

Ref.	Type	Sensing / localization	Communication	Relevance and limitation
[1]	Survey, industrial wearables	Monitoring, supporting, training, tracking classes	Surveyed technologies	Taxonomy and challenges; not an implementation
[2]	Review, mining wearables	Wearable classes; proposed miner safety system	Not detailed here	Concept-level proposal
[3]	Technology review (NIOSH)	Person-down detection; UWB tracking	Wireless sensor networks	Early review; dedicated infrastructure
[4]	Systematic review, underground mines	Location, physiological/kinematic, environmental	Wireless sensor networks	Organizes the field; no single prototype
[5]	Mine IoT system	Vital-sign bracelet, multi-gas lamp, UWB tags	Bluetooth, 5G, UWB base stations	Reported sub-0.3 m deviation; dedicated infrastructure
[6–8]	RSSI localization surveys and method	Wi-Fi RSSI fingerprinting	Existing Wi-Fi APs	Accuracy depends on radio map and environment
[9]	Threshold fall detection	Trunk tri-axial accelerometer	Offline analysis	Simulated falls; limited field evidence
This work	Prototype design	ESP32-S3: AP RSSI zones, MAX30102, MPU6050	Wi-Fi, HTTP, Socket.IO	Existing Wi-Fi; protocol in Sec. VII

V. METHODOLOGY

A. Wi-Fi RSSI-Based Zone Estimation

Let R be the set of registered APs. Each is identified by its BSSID and mapped to a zone $\zeta(j)$, and $RSSI(j)$ is the value in dBm measured for AP j in a single scan. With a configured threshold θ , the reference rule used here selects the strongest registered AP that clears the threshold:

$$z^* = \zeta(\arg\max RSSI(j)), j \in R, RSSI(j) \geq \theta \quad (1)$$

When no registered AP clears θ , the zone is reported as unknown. Two stabilizers can be added in a deployment: a median over the last N scans, and a hysteresis margin Δ (dB) that must be exceeded before a zone change is accepted.

Calibration means recording RSSI at several marked positions in every zone, over repeated scans and at different times of day, and picking θ from the distributions observed. Errors come from several sources: multipath propagation, shadowing by the worker's own body, signal fluctuation, and overlapping AP coverage near zone boundaries, which can place a worker in the wrong zone. The instability of RSSI in changing environments is well documented [7]. Note that the rule outputs a zone label, not coordinates.

B. Physiological Monitoring

The MAX30102 has red and infrared LEDs and a photodetector set up for reflection [12]. Its PPG signal has an AC component that follows the heartbeat over a DC baseline [11]. After filtering, heart rate is estimated from the interval between successive pulse peaks. SpO2 is usually estimated from the ratio of ratios $R = (AC_{red}/DC_{red})/(AC_{ir}/DC_{ir})$ using an empirically calibrated mapping. Signal-quality checks (skin or finger contact, amplitude, motion artefact, out-of-range values) should flag a reading as invalid instead of reporting it. Motion affects wrist or chest placement more than a fingertip, so the estimates still need validation.

The MAX30102 cannot measure blood pressure, and the prototype makes no such claim. For this reason, the blood pressure column of the dashboard stays empty and shows a dash. Measuring blood pressure would require a dedicated, validated device with a documented data interface.

C. Fall Detection

The MPU6050 [14] provides three-axis acceleration (a_x, a_y, a_z) over a programmable full-scale range. The acceleration magnitude is $a_{mag} = \sqrt{a_x^2 + a_y^2 + a_z^2}$ (2)

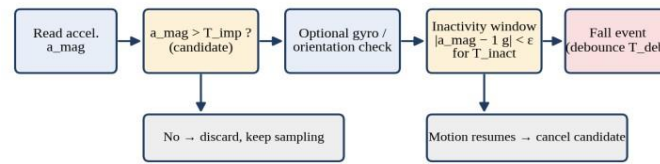


Fig. 3. Illustrative threshold -based fall -event pipeline.

In the pipeline of Fig. 3, a candidate event is raised when $a_{mag} > T_{imp}$. The gyroscope can then be consulted for a change in angular rate or orientation. The fall is confirmed only if the next window of length T_{inact} shows little movement, that is $|a_{mag} - 1 g| < \epsilon$. A debounce interval T_{deb} prevents one event from triggering repeated alerts. In [9] one threshold on a trunk accelerometer separated simulated falls from ADL. Threshold methods can still raise false alarms, for instance when the device is dropped or the work involves vigorous movement, and they can miss slow falls and soft landings, so they must be calibrated by experiment [10].

D. Communication and Real-Time Processing

Each telemetry message should include a device identifier, a device timestamp, heart rate and SpO2 with validity flags, the estimated zone (or the raw AP list), battery state and a fall flag. The backend checks the required fields, adds a server receive time, stores the record, updates the worker's state and emits Socket.IO events to connected dashboards. A worker becomes stale when nothing has arrived for T_{stale} and offline after a longer silence; the dashboard in Section VI uses a stale limit of 30 s. Lost packets and network interruptions delay or drop alerts. Buffering on the wearable and retransmission reduce the losses but add latency and need memory. When a Socket.IO connection drops, the dashboard should resynchronize its state once it reconnects.

E. Safety Alerts

The system raises three kinds of alert: a fall event, an offline or stale-telemetry condition and, where configured, an abnormal reading. An open incident is deduplicated per worker and type. An administrator acknowledges and resolves it, and it stays in the history. A detected event is what a classifier produced, not a confirmed accident, so a person must check it. If the node loses its Wi-Fi link, a fall detected locally cannot reach the dashboard until the link returns. A missing alert therefore does not prove that a worker is safe.

TABLE II. System Modules

Module	Technology	Function	Input / output
Node	XIAO ESP32-S3	Acquire, detect, send	Sensors / HTTP
HR, SpO2	MAX30102	PPG sensing	Light / raw counts

IMU	MPU6050	Motion sensing	Motion / accel., gyro
Zoning	AP RSSI scan	Zone label	AP list / zone
Backend	Node.js, Express	Validate, alert	JSON / events
Storage	Database or file	Persist records	Records / history
Real time	Socket.IO	Push events	Events / UI
Dashboard	React, Vite	Display, acknowledge	Events / actions

VI. IMPLEMENTATION

Table II lists the modules of the design. Pin assignments, sampling rates, transmission intervals and power figures are deployment parameters set during calibration, and they are not reported here.

A. Administrator Dashboard

The administrator dashboard is a React application fed by

Socket.IO. Its sidebar offers seven pages: Overview, Live Monitoring, Zones, Health, Incidents, Workers and Devices. Figs. 4–6 are screenshots of the running application. They were taken with four registered demonstration workers driven by simulated data (tagged SIM or DEMO in the interface) and with no live wearable node connected, so every device shows as offline. The figures illustrate the interface and its behaviour. They are not measurements of the system.

The Overview page (Fig. 4) starts with six counters: registered workers, workers online, workers offline, active health alerts, active fall incidents and configured zones. If a fall incident is waiting for acknowledgement, a red banner appears; here it names WORKER-001. Underneath, one table gives each worker's zone, heart rate, SpO2, link status and time since the last update, and beside it a list shows open incidents with severity and a repeat count. Zone occupancy is marked as an estimate, with a note that it is derived from Wi-Fi RSSI at configured access points and is not GPS-grade positioning.

The Live Monitoring page (Fig. 5) adds search by ID, name or department, zone and status filters, and columns for fall state, link state and alert count. Colours carry meaning: green for normal and fresh values, amber for a warning threshold or stale data, red for a critical value or an active fall, and grey for an offline worker or one without a valid reading. On the Health page (Fig. 6) an operator sets the minimum and maximum heart rate and the minimum SpO2 (45 bpm, 120 bpm and 94 % in the screenshot). The page lists active health alerts and shows live vitals with signal quality, sensor validity and freshness. Invalid or missing readings appear as a dash and are never filled in with a guess. A breach raises one alert per worker and condition, and recovery does not close it automatically; an operator decides. The page also notes that the system is not medical-grade equipment.

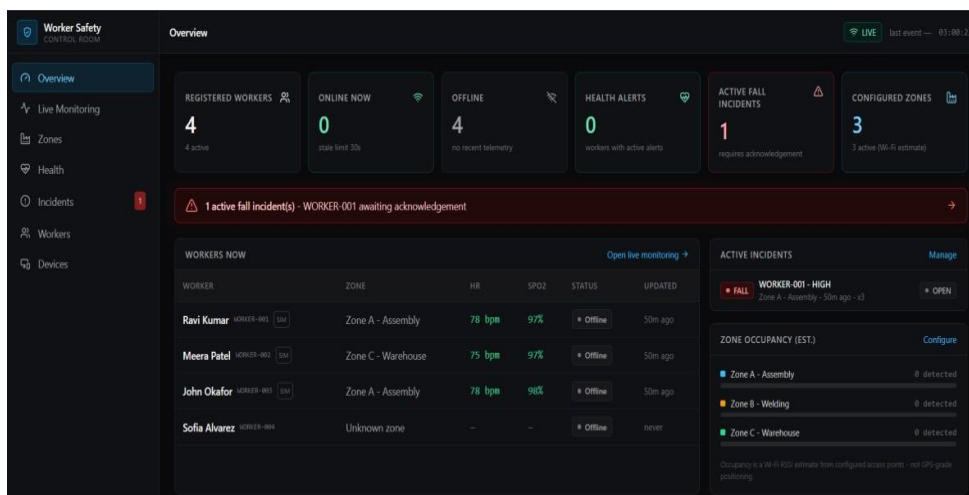


Fig. 4. Overview page of the control-room dashboard with simulated workers: status counters, fall-incident banner, worker table, open incidents and estimated zone occupancy.

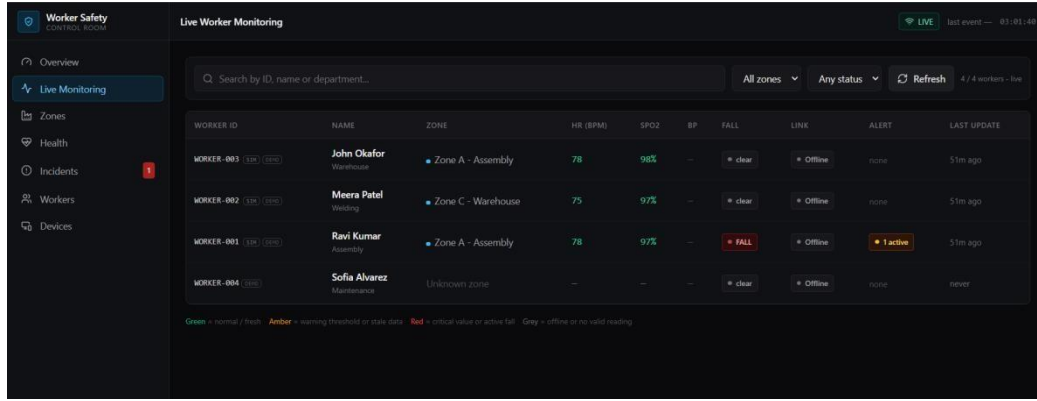


Fig. 5. Live Monitoring page showing zone, heart rate, SpO2, fall, link and alert state for each worker.

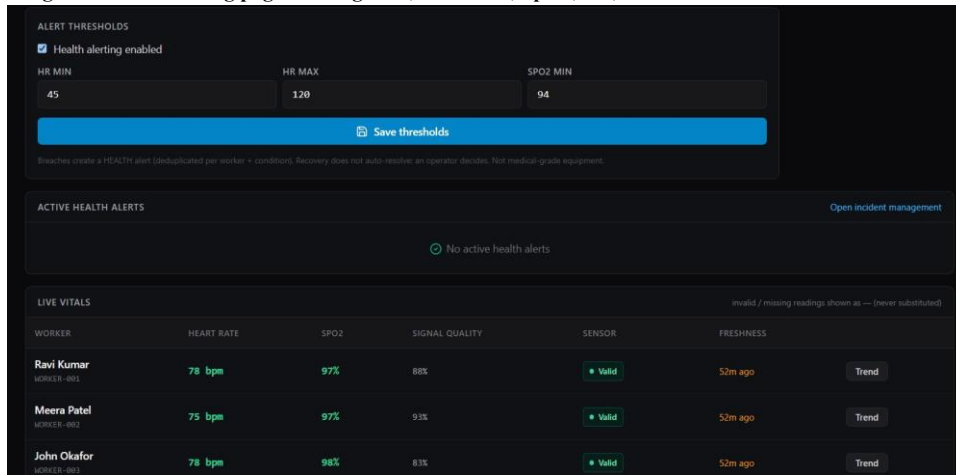


Fig. 6. Health Monitoring page with configurable alert thresholds and live vitals including signal quality and sensor validity.

VII. EXPERIMENTAL SETUP AND EVALUATION

A. Protocol

Zones (RQ1). Define K zones, each with at least m test positions. Over repeated trials at several times of day, record the true zone and the reported zone. Stability is measured as the number of spurious zone changes per minute for a stationary worker, and as the delay before the correct zone appears after a walk across a boundary.

Falls (RQ2). Only scripted, supervised and safe simulations are used: controlled lowering onto a crash mat and an instrumented or mannequin drop for impact events, together with scripted ADL (walking, sitting, bending, stair use, tool handling, knocks to the device). Human participants require ethical approval and informed consent, and nobody is asked to fall in a dangerous way.

Physiology (RQ3). Record readings from the node and from a reference pulse oximeter or ECG device at the same time, at rest and during light activity.

Communication (RQ4). Send N_{sent} messages and count how many arrive. Trigger controlled Wi-Fi outages and observe what the backend and dashboard do.

B. Metrics

Accuracy, precision, recall and F1-score are defined as

$$\text{Accuracy} = \text{correct predictions} / \text{total predictions} \quad (3)$$

$$\text{Precision} = TP / (TP + FP), \quad \text{Recall} = TP / (TP + FN) \quad (4)$$

$$F1 = 2 \cdot \text{Precision} \cdot \text{Recall} / (\text{Precision} + \text{Recall}) \quad (5)$$

For falls, a true positive (TP) is a simulated fall that triggers exactly one alert within a window W. A false negative (FN) is a simulated fall with no alert in W. A false positive (FP) is an alert raised during an ADL trial or outside W, and a true negative (TN) is an ADL trial with no alert. The telemetry delivery rate is $N_{\text{recv}}/N_{\text{sent}}$. End-to-end alert latency is $L = t_{\text{dash}} - t_{\text{event}}$, where t_{event} is the moment the impact is applied (taken from a trigger logged on a reference clock) and t_{dash} is the moment the dashboard shows the alert; both are logged against one synchronized clock. Offline-detection time runs from the last delivered packet to the offline flag. Agreement with a reference instrument is assessed by the bias $\bar{d}$ and the limits of agreement $\bar{d} \pm 1.96 \cdot s_d$ of the paired differences d_i (Bland-Altman analysis), and the mean absolute error is reported too.

TABLE III. Measurement and Reporting Plan

Quantity	Method	Reported as
Zone accuracy	Confusion matrix over K zones	Accuracy, per-zone recall
Zone stability	Stationary and boundary crossing trials	Changes per minute; delay
Fall detection	Labelled simulated falls and ADL	TP/FP/FN/TN, precision, recall, F1
HR, SpO2	Paired readings vs. reference	Bias, limits of agreement, MAE
Delivery rate	N_{recv} / N_{sent}	Rate per network condition
Alert latency	Common reference clock	Median, 95th percentile
Offline detection	Last packet to flag	Seconds

VIII. PLANNED ANALYSIS

Table III shows how each measurement will be analyzed and reported. Results will be given with sample sizes, test conditions and repeated trials, and we will claim nothing beyond what the data support. Zone results will be compared against the RSSI literature [6], [7], and fall results against the threshold-method evidence from simulated data [9], [10]. We will also examine false alarms, missed events, RSSI fluctuation, sensor quality, battery limits, communication loss and how well the system scales to many workers.

IX. LIMITATIONS AND THREATS TO VALIDITY

Localization: RSSI yields coarse zones, not coordinates, and it reacts to the environment [7]. Sensing: optical estimates depend on skin contact, motion and placement, and they have not been clinically validated. Falls: threshold detectors exchange false alarms for missed events, and simulated falls differ from real ones [10]. Connectivity: remote alerts need network coverage, which underground or shielded areas may lack. Power and comfort: battery runtime and wearability have not been measured. Security and privacy: health and location data call for authentication, encrypted transport, access control and a data-protection policy, and we claim none of these. Dashboard: the screenshots in Figs. 4–6 come from simulated workers, show the interface only and are no evidence of detection performance. External validity: small samples and a single test site limit how far the results generalize. A research prototype is not a safety-critical production system. It lacks certification, formal hazard analysis, redundancy and fail-safe behaviour, and it must not replace established safety procedures.

X. CONCLUSION AND FUTURE WORK

We have presented the architecture, the formal methods and the evaluation protocol of a wearable IoT prototype that joins Wi-Fi zone estimation, optical heart-rate and SpO2 sensing, and fall-event detection to a real-time administrator dashboard, which is implemented and shown in Figs. 4–6. The protocol fixes the datasets, metrics and clock discipline needed to evaluate the system repeatably. Empirical results remain to be reported. Next steps are to run the protocol in the field, add access points or calibrated localization, improve fall classification, integrate a validated blood-pressure device, deploy secure industrial gateways, add local emergency notification with offline buffering and cut energy use.

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