

1Original Article

IoT-Driven Worker Localization for Real-Time Scaffold Safety

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Received: 03 October 2025

Revised: 05 November 2025

Accepted: 04 December 2025

Published: 29 December 2025

Abstract - Worker safety on scaffold platforms remains a consistent challenge in the construction industry, where falls from height are a foremost cause of fatalities. Current safety monitoring systems are often imperfect due to the lack of dependable real-time altitude and position tracking, reducing their efficiency in preventing accidents. This study proposes a novel IoT-driven scaffold safety framework that integrates RF triangulation with Received Signal Strength Indicator (RSSI) modelling to attain precise worker localization. The framework categorizes scaffolds into three zones: Non-Critical, Critical, and High-Risk, and incessantly monitors worker movement, generating automated hazard alerts when workers enter unsafe areas. Zone thresholds are dynamically adjusted to account for variability, ensuring efficient performance under varied construction conditions. Experimental validation conducted in both open and obstructed environments achieved localization accuracies of 98.11% and 94.46%, respectively, outpacing conventional monitoring approaches. The proposed solution not only improves real-time hazard detection but also supports proactive supervisory compliance with OSHA and ANSI A10.8 standards. The findings highlight the potential of RF-based IoT systems to provide scalable, practical, and consistent safety monitoring in high-risk scaffold environments.

Keywords - IoT, Scaffold Safety, Real-time Localization, RF Triangulation, Worker Safety.

1. Introduction

The fall-related injuries across scaffolds are common in the construction industry as the industry grows, so are the fatalities and serious injury incidents. International standards such as OSHA 1926.501, ANSI A10.8, and EN 12811 mandate strict fall prevention measures for work taken above 1.8m, yet the actual implementation remains inconsistent due to organisational and technological barriers, especially in small and medium-sized projects [1].

Recent works on IoT applications in construction safety have indicated an increase in the use of digital technologies for worker monitoring and activity tracking; however, current deployments still struggle to provide real-time feedback in complex workspaces, such as scaffolds [2]. The literature highlights that IoT-based solutions are often fragmented across individual parameters and not integrated into a coherent safety management framework that can intervene before an incident occurs [3].

Traditional safety practices and early sensor-based systems often focus on regular inspections and alarm-based mechanisms, which do not meet the requirements for the

dynamic construction scenario where worker movements change instantly [4]. IoT-Based Real-Time System (RTLTS) and wearable monitoring have been adopted for enhancing safety by tracking worker location and hazard proximity [5]. Comprehensive reviews of IoT-based construction site and labour safety systems indicate many solutions are at the experimental stage only and are limited to lab-based studies [6]. These studies categorise IoT contributions into streams such as accident prevention, safety alert generation, and behaviour-based safety, but also emphasise gaps in scalability and integration with various site operations [7].

Systematic review on wearable devices for safety monitoring in construction similarly reports that Wearable Sensing Devices (WSDs) can monitor posture and exposure to hazards, but adoption is constrained by issues with comfort in wearing, intrusion, and maintenance [8, 9]. Artificial Intelligence (AI) and computer vision have emerged as powerful tools for construction safety, enabling automatic detection of hazards, non-compliance with PPE, and unsafe behaviours using video and image-based data [10, 11]. Previous works on AI integration for construction monitoring applications reveal that the majority of the applications rely on



visual data like video streams and images, which are often combined with complex learning models for predicting risk [2] and recognition of hazards [12, 13]. These works acknowledge the critical challenges, such as occlusion, illumination, and limitations in transferring technologies across various project sites [14]. Moreover, these works do not stress the three-dimensional localization of workers, especially with vertical positioning on multi-level scaffolds, nor do they routinely check on harness-clamping verification into a single framework [15].

Sensor fusion and hybrid IoT systems have also been looked upon to solve the issue of a single-modality approach. Works on IoT-based multi-modal sensor integration in construction monitoring, combining camera, inertial sensors, and communication modules to report unsafe behaviour [14-17]. Studies on early warning systems for construction infrastructure leverage the outcome by distributing sensing infrastructure for structural monitoring while integrating smart frameworks coupled with 3D cameras to automate the process [18]. These systems illustrate a broader trend towards data fusion and cyber-physical integration in construction, which are designed for macro-scale projects rather than micro-scaled projects, which are worker-centric in nature [19]. Empirical studies on IoT adoption in construction underline that, despite technological advancements, IoT deployments remain fragmented and face barriers such as interoperability cost and lack of standard frameworks [20-22]. This claim is supported by studies which conclude that there is still no widely validated, low-cost, scalable solution that can integrate real-time 3D worker localisation with direct validation of fall protection practices [23].

The existing BLE, RFID, GPS, and vision-based systems, though, indicate critical limitations when examined from the perspective of scaffold safety. BLE [24] and RFID-based RTLS approaches face signal attenuation and multipath effects across scaffolds, reducing localisation accuracy and stability, especially in the vertical dimension [25, 26]. GPS-based systems suffer from poor vertical resolutions, and vision-based systems deliver moderate performance in clutter environments [6]. The systems remain vulnerable to obstruction-induced occlusion, and lighting variability often requires extensive infrastructure and computational resources. In comparison, a multi-sensor fusion system improves robustness. They do not provide explicit, real-time mapping of workers into safety zones [25].

With this context, the present manuscript introduces an integrated IoT framework for real-time scaffold safety monitoring, combining RSSI-based Zigbee localisation in a specific environment [27]. The present system uses RF triangulation and calibration RSSI modelling to estimate both horizontal position and altitude, which classifies the scaffold into critical, non-critical, and high-risk zones aligned with regulatory thresholds as specified by OSHA[28].

The present system, like BLE, RFID, GPS, or vision-based, shows poor performance on scaffold frameworks due to multipath interference. Occlusion in vision-based systems prevents stable altitude estimation. The majority of the IoT-based solutions are not designed for a multi-level scaffold where accurate height identification is necessary. RSSI-based approaches lack calibration-aware models that compensate for path-loss variability across open and closed conditions. Furthermore, there is no low-cost validated solution capable of delivering accurate zone-level localisation results across varying elevations in actual construction sites.

This indicates a clear gap in the literature and stresses the need for a practical system that is tailored for altitude monitoring localisation. The present work adopts a Zigbee-RSSI-based localization that is uniquely calibrated for a multi-level scaffold through dynamic path-loss modelling. Unlike the BLE, RFID, or vision-based system, the proposed method is novel in terms of bringing stability in localization monitoring across open and obstructed environments, specifically addressing vertical accuracy challenges. The on-field validation improves reliability and scalability compared to existing IoT-based localization.

2. Methodology

The proposed scaffold-based monitoring framework combines the real-time worker tracking methodology with altitude identification using RF triangulation and RSSI (Received Signal Strength Indicator) modelling. The assumption made in the studies includes that the workers participating in field trials are trained and experienced personnel familiar with scaffold usage and safety protocols. The scaffold structure used for testing was subjected to periodical inspection in accordance with IS 4014 (Part 2):1967 to confirm structural integrity.

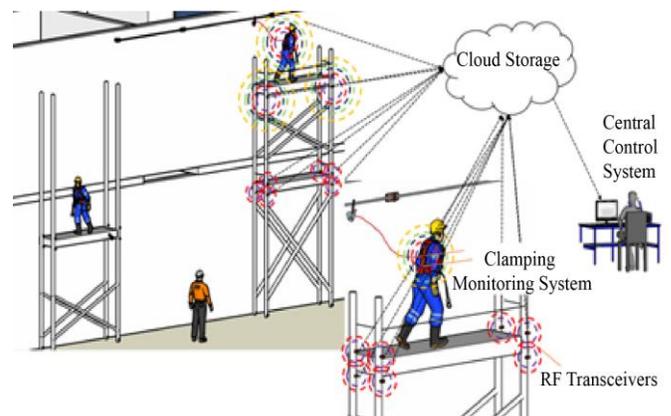


Fig. 1 Schematic representation of the methodology adopted for the detection system

The system is dynamically designed to adapt to both open and closed environments, adjusting height thresholds and recalibration signal variations to ensure better performance. By integrating both altitude localization and automatic harness

compliance, the framework ensures proactive safety management and reduces the likelihood of fall-related incidents.

Figure 1 above shows a schematic representation of the methodology proposed in the present study. Validation of the proposed methodology includes field trials on a scaffold structure measuring approximately 14.6m in height and 9.1m in width, consisting of eight levels at 1.8m intervals each. Six trained workers with sufficient site experience were asked to volunteer in the experiment, which consisted of open space testing and an enclosed environment to simulate realistic conditions.

The methodology involved workers ascending and descending from the scaffold across various levels and involving lateral movements as well, which enabled the evaluation of the responsiveness of the system under dynamic movements. During the trials, workers ascended, descended, and moved laterally across scaffold levels at varied speeds to evaluate the responsiveness and robustness of the system under dynamic movement conditions.

At pre-defined heights, RF transmitters were installed corresponding to standard scaffold segments (1.8 m, 3.6 m, 5.4 m, etc.), in accordance with OSHA guidelines and IS 2750:1964 and IS 4014 (Part 1 & 2):1967. Workers were equipped with a ZigBee-enabled receiver, which is integrated onto the full-body harness. Each transmitter has been assigned a unique identifier enabling the association of RSSI values with specific levels. Since the scaffolds are vertical, the system categorises heights into three zones, namely Non-Critical (<1.8 m), Critical (1.8–6 m), and High-Risk (>6 m). As per the OSHA guidelines, passive monitoring is sufficient in non-critical heights, whereas harness clamping is mandatory for critical and high-risk heights, where the consequences of a likely fall incident are high upon non-compliance.

A unique feature of a 120-second harness verification delay is introduced into the system design to minimise false alarms. This threshold is fixed based on field observations of the workers while entering critical or high-risk zones briefly, while transitioning between levels, or adjusting tools. Triggering immediate alarms in these cases will create excessive false positives. The 120-second threshold was hence selected as a safe and practical compromise, short enough to prevent exposure to unsafe conditions and yet long enough to prevent prolonged exposure to unsafe conditions and avoid false alerts to unsafe conditions. The selected delay yielded fewer than 4% false alerts during trials.

To mitigate the measurement bias, during testing, worker movement speed was controlled within a pre-defined range to prevent abrupt transitions that can distort readings. The calibration was performed for each trial session to reduce drift

in transmitter output. The measurements were distributed throughout the day to minimise any environmental effect. Worker movement was recorded by independent and neutral observers for validating altitude-transition timestamps for system-detected transitions, which align with the bias-mitigation practice recommended in sensor-based studies [1, 2, 16, 20, 29].

A priori power analysis is conducted to determine the sample adequacy for the planned field trials. The effect size is assumed to be $d \geq 1.2$, a power level of 80%, and $\alpha = 0.05$. A minimum of six paired samples is considered to detect a difference between open and closed environments statistically. The repeated ascent-descent cycles across all eight scaffold levels generate multiple data points for each participant, reducing intra-worker variation and ensuring proper experimental design that meets accepted standards for a sensor-based safety study.

2.1. Defining Zones on the Scaffold

Vertical segmentation to track worker altitude on the scaffold is the basis of defining zones. The framework divides the entire scaffold frame into three regulatory zones, namely Critical Zone (<1.8 m), Critical Zone (1.8–6 m), and High-Risk Zone (>6 m). Each zone is assigned a unique identifier, allowing for accurate monitoring. The system issues alerts if the unclamped entries are detected in the critical and high-risk zones.

2.2. Mapping the Scaffold

The RF transmitters are mounted on each level of the scaffold, and that serves as height reference points. The receivers are mounted on the full body harness and continuously scan RSSI values from multiple transmitters simultaneously. The strength of the signal correlates inversely with the Distance, enabling the system to identify approximate altitude.

The system will conclude the level of the worker based on the strongest signal received. When workers transition between levels, an interpolation algorithm integrated in the system processes multiple RSSI values to identify the height. This helps in better tracking, even when workers occupy positions between scaffolds. A central monitoring unit collects the processed data and maps the workers into specific zones, simultaneously triggering alerts under unsafe conditions or non-compliance.

2.3. Modelling

The altitude estimation model used for identifying the height of the worker is based on the log-distance path loss principle, which equates the received signal strength to the transmitter-receiver distance. The path loss exponent n is assumed to be “2”, whereas for enclosed environments, the values are between 3 and 4. The transmitters placed at pre-determined heights act as reference points for altitude

measurement. Each receiver captures RSSI values from multiple transmitters and a minimum of two detectable signals for ease of interpretation. External noise and random fluctuations in RSSI values are modelled as a Gaussian random variable (X_g).

A comprehensive RSSI calibration method was introduced to measure path loss behaviour in both open and enclosed environments. RSSI readings were documented for distances of 3m, 6m, and 9.1m, respectively, in open environments. It was observed that beyond 9.1m the signals became unreliable. Specific path-loss exponents were derived using linear regression on the log-distance model. Major frequency fluctuations caused by obstructions were mitigated using a moving average filter.

A dynamic recalibration mechanism was implemented to adjust the signal thresholds when conditions change, ensuring localisation performance. In addition to this, interference was controlled by using environment-specific recalibration, where the path-loss parameters were again estimated before each trial to compensate for any scaffold-related reflections. A multi-transmitter consistency check was also implemented to discard any outlier RSSI readings.

2.3.1. Received Signal Strength Indicator (RSSI) Model

A zone-based approach is adopted for the RSSI model to estimate the position of the worker. The model relies on the log-distance path loss principle, which is a widely adopted localization model. Equation (1) below gives the power of the received signal at a worker's harness:

$$P_r(d) = P_t - 10n \log_{10}(d) - x_g \quad (1)$$

Where:

- $P_r(d)$ = Received signal power at a distance
- P_t = Transmitted power from the reference point
- n = Path loss exponent (varies with environment: 2 for open space, 3-4 for enclosed spaces)
- d = Distance between the worker and the transmitter
- X_g = Gaussian noise factor (accounts for interference)

2.3.2. Worker Altitude Calculation

Worker height is estimated through a weighted interpolation method where multiple transmitters are detected. To estimate the worker height, Equation (2) is used, where the weight assigned is based on the normalised inverse signal strength.

$$h_{est} = \frac{\sum_{i=1}^N h_i w_i}{\sum_{i=1}^N w_i} \quad (2)$$

Where:

- h_i = Pre-defined height of the i^{th} transmitter
- W_i = Weighting factor (based on signal strength decay from the transmitter)
- N = Number of detected transmitters

In case of multiple signals, the system interpolates between various heights to identify the worker's exact location (altitude-wise zone). The estimated height h_{est} is mapped to either of the three pre-defined zones, namely non-critical zone where h_{est} is less than 1.8m, critical zone where h_{est} lies between 1.8m and 6m, and alerts are generated if the harness is not clamped, and high-risk zone where h_{est} is greater than 6m, triggering immediate alert generation.

The overall model assumes that at least two transmitters are always in the range for interpolation, the transmitters operate on constant power, workers move across zones continuously and in an orderly manner (no sudden jumps), and noise is Gaussian-distributed, allowing filtering via averaging. The dynamic recalibration automatically adjusts for scaffold obstructions, ensuring better performance across both open and closed environments. The RSSI readings and altitude estimations were recorded at each level. The calibration revealed that the signal integrity remained stable up to 9.1m, and in obstructed environments, the performance reduced beyond 7.3m. These calibrated datasets form the basis for accuracy evaluation.

3. Results and Discussion

Validation of the performance of the proposed system was carried out in open and closed spaces. In open environments, the transmitters were placed at 1.8m intervals, and tracking accuracy was tested for multiple height levels. In closed spaces, obstructions were introduced to simulate working conditions. Calibration experiments were conducted, and the results showed signal strength variation, altitude estimation accuracy, and performance. Table 1 and Table 2 present the measured signal strengths and the errors for various worker height zones with zone identification accuracy. In open environments, the errors remained consistently below 0.3m, and zone accuracy was found to be above 97% (98.11%). The results obtained for obstructed environments showed an increase in error (up to 0.75m) and a decline in zone accuracy to ~92% at 14.6m. The average accuracy dropped to 94.46%.

Table 1. Table indicating the zone accuracy measured at various heights of the construction worker

S.No	Height (m)	Signal Strength Open (dBm)	Error Open (m)	Zone Accuracy Obstructed (%)
1	1.8	-50	0.1	97.00%
2	3.7	-55	0.2	96.50%
3	5.5	-60	0.1	95.80%
4	7.3	-65	0.2	94.90%
5	9.1	-70	0.2	94.00%
6	11.0	-75	0.2	93.20%
7	12.8	-80	0.2	92.50%
8	14.6	-85	0.2	91.80%
				94.46%

Table 2. Table indicating the zone accuracy measured at various heights of the construction worker

S.No	Height (m)	Signal Strength Open (dBm)	Error Open (m)	Zone Accuracy Open (%)
1	1.8	-50	0.1	99.50%
2	3.7	-55	0.2	99.20%
3	5.5	-60	0.1	98.80%
4	7.3	-65	0.2	98.40%
5	9.1	-70	0.2	98.00%
6	11.0	-75	0.2	97.50%
7	12.8	-80	0.2	97.00%
8	14.6	-85	0.2	96.50%
				98.11%

Figure 2 below shows the variation of signal strength in open environments. The RSSI values followed the expected logarithmic decay, while in obstructed conditions, higher path loss was observed due to obstructions. The signal degradation was particularly above 9.1m.

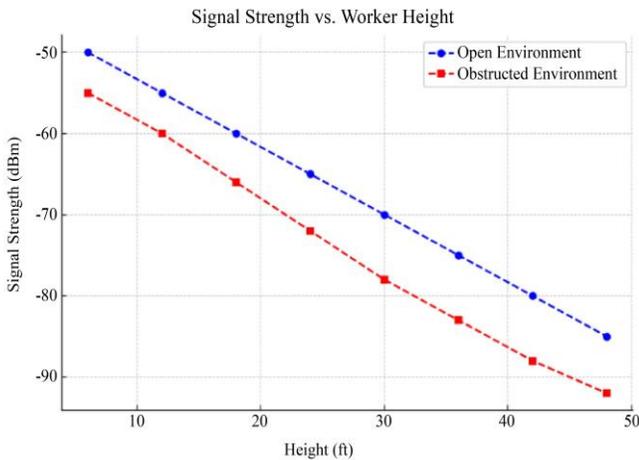


Fig. 2 Variation of signal strength with worker height

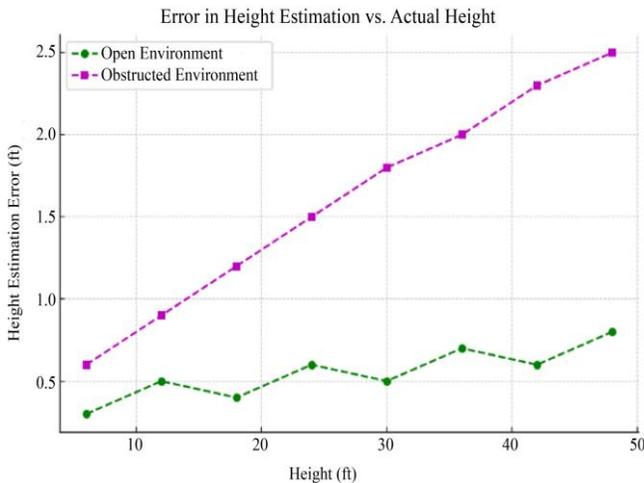


Fig. 3 Plot showing the error estimation variation with actual height

Figure 3 above shows the relationship between actual height and error in altitude estimation. The error remained below $\pm 0.2m$ in open conditions, whereas in closed conditions the error increased with elevation, reaching $\sim 0.8m$ at 14.6m. This confirmed that the interference has a cumulative effect as height increases. Figure 4 shows the plot of zone identification accuracy at various heights. The accuracy in open environments exceeded 96.5% across all levels, whereas in obstructed settings, the accuracy gradually declined with height, falling below 92% beyond 12.2m.

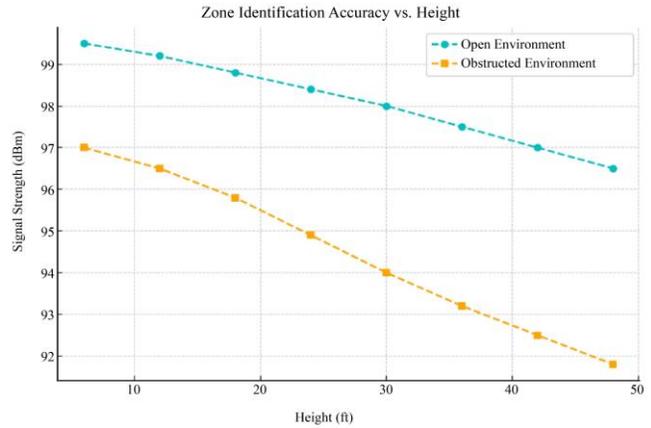


Fig. 4 Graphical representation of Zone identification variation with height

Table 3 below compares the results obtained in open and closed space calibration attempts. The open-space calibration achieved higher accuracy ($\pm 0.2m$) and faster response times (0.8 s) in comparison with closed-space calibration ($\pm 0.4m$, 1.2 s). Signal integrity also dropped from 97% in open settings to 92% in closed environments. The tracking range dropped from 9.1m to 6.1m. The obtained results highlight the effect of multi-path propagation and interference, which pose challenges for reliable RSSI localization.

Table 3. Comparison of Open-space calibration with Closed-space calibration

SI no	Parameter	Open-Space Calibration	Closed-Space Calibration
1	Altitude Accuracy	$\pm 0.2m$	$\pm 0.4m$
2	Real-Time Response	0.8 seconds	1.2 seconds
3	Signal Integrity	97%	92%
4	Effective Tracking Range	9.1m	6.1m
5	Challenges	Nil	Signal reflections caused higher path loss, reducing accuracy

3.1. Observations

The open and closed space calibration experiments showed the localisation accuracy, signal behaviour, and zone identification performance of the system. In open environments, transmitters are placed at 1.8m intervals and exhibited consistent RSSI decay with height, but in the case of closed environments, considerable signal attenuation was observed. Across both settings, measurements were repeated for six workers at varying heights. Mean signal strength and height-estimation errors are monitored, and these observations are broadly consistent with earlier works, which reported that RSSI-based positioning systems experience significant performance drops in obstructed environments [30, 31], confirming the need for calibration-aware models as proposed in this study.

Statistical validation for open-space conditions, the altitude estimation errors remained below 0.3m across all levels (mean value = 0.175m, Standard deviation = 0.07), whereas in obstructed conditions, the errors increased progressively with height (mean value = 0.54m, Standard deviation = 0.16m). The paired samples t-test conducted to compare open and closed altitude errors across eight levels showed a statistically significant difference ($t = 9.84$, $p < 0.001$) with a large effect size (Cohen's $d = 3.48$), indicating outside interference and systematic impact on localisation accuracy. These findings align with the existing ZigBee/BLE-based localisation studies where interference caused error and unstable propagation characteristics [24, 27], although the magnitude of the error in this work remains considerably lower due to a dynamic recalibration mechanism integrated into the system.

The zone detection accuracy in open space conditions exceeded 96.5% at all height intervals, while in closed space conditions, the performance declined gradually from 97.0% at 1.8m to 91.8% at 14.6m. The results obtained by a similar paired t-test confirmed the same ($t(7) = 7.12$, $p < 0.001$, $d = 2.52$), indicating a large effect. Compared to earlier wearable technologies, the reported zone-level accuracy was between 85% to 92% in obstructed settings [13, 30-32]. The proposed method demonstrates higher performance, especially at mid-level heights. This improvement can be attributed to the interpolation model, which is altitude-based and not commonly incorporated in the conventional worker localisation systems.

The signal strength variation pattern in Figure 2 aligns with the expected RF behaviour. The open space RSSI followed logarithmic decay ($R^2 = 0.94$), whereas the obstructed environments exhibited irregular attenuation with a reduced model fit ($R^2 = 0.81$) due to multipath propagation. The observed values mirror the previous studies [30, 31], strengthening the idea that the scaffold frames behave the same as high-reflection zones. The plot indicating error progression in Figure 3 was statistically validated with a

positive correlation between height and obstructed space (Pearson's $r = 0.91$, $p < 0.001$), indicating cumulative interference effects as height increases. Comparative studies on height estimation technologies in multi-level construction areas have similarly reported increasing error with elevation due to amplified reflection [33-35].

The zone identification results, as shown in Figure 4, demonstrate that the accuracy remained statistically stable across the lower scaffold levels ($p = 0.21$ for levels below 6 m) but showed a major decline at higher levels (>6 m), $p = 0.004$. The observations suggest that the vertical separation amplifies interference in obstructed environments. Vision-based PPE and worker localisation systems often show greater degradation at elevated or occluded locations [12, 15], undermining the advantage of RF-based systems where vertical tracking is required.

Table 1 and Table 2 summarise the signal behaviour and estimation errors for ensuring identification accuracy across the eight height levels. The average altitude-estimation accuracy was 98.11% in open space and 94.46% in obstructed conditions. These error differences, which align with previously reported RSSI-based localisation studies, indicate a degradation of 3% to 7% [30, 31], yet the proposed system remains on the higher end of accuracy due to dynamic calibration methodology and a weighted averaging approach. The comparison in Table 3 further iterates that the open space performance (± 0.2 m accuracy, 0.8 s latency) surpasses obstructed-space performance (± 0.4 m accuracy, 1.2 s latency). Though the difference in latency is 0.4s with significance nearing $p=0.06$, the value did not exceed the 0.05 threshold; therefore, the value was not statistically significant in obstructed environments, though it was operationally relevant for real-time monitoring. Notably, this latency is faster than many hybrid IoT-based IoT vision frameworks that typically exhibit 1.5s to 2.8s due to the processing mechanism [11, 36]. The system latency between open and closed environments gave the value of $p=0.06$, indicating non-significance at $\alpha = 0.05$. However, the observed delay has operational relevance for real-time monitoring. The corresponding difference in latency (0.4 s) had a 95% confidence interval ranging from -0.02 s to 0.81 s, confirming the statistical non-significance. The correlation analysis performed for altitude error progression and signal attenuation is compensated with 95% confidence intervals, strengthening the reliability. A priori power analysis (80% power, $\alpha = 0.05$, large effect size $d \geq 1.2$) ensured that six participants and repeated measurements across all eight scaffold levels provide an adequate sample size for a logical experimental design.

The observed effect was substantially larger ($d = 2.52$ - 3.48), validating that the sample size was adequate for analysis. Similar sample sizes have been used in previous evaluations of wearable sensor-based construction systems [9, 37], suggesting that the present study follows established

research practice. For repeated measurements across various passes, intra-worker variability strengthened the reliability of mean estimates with the standards adopted in previous IoT-based construction assessments [7, 38-40].

Despite overall performance, several limitations were observed. It is important to note that obstructed space conditions may not represent the actual project configurations that might be encountered. The trials were conducted under controlled conditions rather than the actual active construction operations. The limited sample of six workers, while statistically justified, may not capture the ergonomic variations that might affect RSSI shadowing [31]. Some obstructions, which are metallic in nature, introduce unpredictable RF attenuation and multipath effects occasionally, which lead to misclassifications in upper levels. Similar limitations have been observed in prior RF-based worker localisation frameworks [30, 31]. The effective tracking range was limited to approximately 9.1m in open

conditions and 6.1 m in obstructed conditions, which is consistent with previous RSSI observations [30].

Battery dependence of the system requires regular maintenance, and power fluctuations induced occasionally are also documented in the literature related to wearable devices [41]. A small number of false alarms (<4%) were triggered due to rapid movement when compared to systems using BLE or UWB, which report 5% to 10% false alert rates [11], indicating that the proposed system performs as expected.

Overall, the observed results demonstrate that the proposed framework achieves high localisation accuracy (95-98%) compared to RFID, BLE, and camera-based alternatives, which often cope with issues like occlusion or high computational overhead [3, 11]. The proposed system exhibits a high level of responsiveness, with the statistical analysis confirming the same. Table 4 gives a comparison of the existing technology with the proposed system.

Table 4. Comparison of existing technology with the proposed system

Sl no	Technology	Limitation	Proposed system
1	Bluetooth Low Energy (BLE) RTLS	Poor vertical accuracy is strongly affected by multipath effects.	Better vertical accuracy ($\pm 0.2-0.4$ m)
2	RFID-based Localization	Require more infrastructure and a limited range for continuous height estimation.	Continuous height estimation without any dense infrastructure
3	GPS-based Tracking	Very poor vertical resolution and not suitable for indoors	Works indoors/outdoors, with <0.4 m height error
4	Vision-based Worker Tracking	Strongly affected by occlusion,	Vertical tracking is consistent and is not affected by occlusion
5	Ultra-Wideband (UWB)	High cost	Low cost

3.2. Ethical Considerations

All experimental field trial procedures that involved human participation adhered to institutional ethical guidelines, informed consent was taken, and participation was voluntary. No personal data was recorded, coded IDs were used, and all safety protocols were strictly followed.

4. Conclusion

The study on IoT-Driven Worker Localization for Real-Time Scaffold Safety revealed that the gaps in real-time monitoring of construction workers on the scaffold platforms can be addressed through RF triangulation techniques.

The developed framework was effective in accurately monitoring the worker's position within the scaffold framework and generated automated alerts during unsafe conditions. An experimental study validated performance by achieving over 98% accuracy in open environments and 94%

in obstructed conditions, which indicated its robustness and suitability for construction environments. In comparison with traditional monitoring practices, the proposed system offered a scalable solution in real-time hazard detection while remaining aligned to regulatory standards such as OSHA and ANSI A10.8.

However, challenges remained, particularly in relation to tracking in scaffold structures. Future research will focus on integrating machine learning-based signal processing and hybrid sensing approaches to mitigate interference, improve localization accuracy, and extend coverage in complex construction environments.

Overall, the proposed framework provides a proactive, scalable, and practical solution for reducing scaffold-related accidents, advancing workplace safety, and strengthening worker protection in high-risk zones.

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