ESP-JETA
ESP Journal of Engineering & Technology Advancements
ISSN: 2583-2646 / Volume 5 Issue 2 May 2025 / Page No: 207-215
Paper Id: JETA-V5I2P122 / Doi: 10.56472/25832646/JETA-V5I2P122

Original Article

Bluetooth Low Energy (BLE)-Based Person Detection for Smart Surveillance and Indoor Tracking

Abhay Mangalore
Software Engineering Manager, Arlo Inc, San Diego, USA

Received Date: 25 February 2025 Revised Date: 02 April 2025 Accepted Date: 23 May 2025

Abstract: *Bluetooth Low Energy (BLE) technology has emerged as a key enabler of smart indoor positioning systems and person detection frameworks, offering low-cost, low-power, and scalable deployments. This article reviews core BLE-based localization principles, including signal attenuation modeling, trilateration, and fingerprinting. We further examine their integration with real-world platforms such as ESP32 microcontrollers and Apple Watch wearables in the context of smart homes, hospitals, and secure buildings. This review also explores BLE's role in security surveillance, multi-resident activity recognition, privacy-aware access control, and BLE mesh networks. Implementation architectures, use cases, equations, and challenges are detailed. Finally, we highlight promising directions in AI-based signal filtering and multi-modal fusion.*

Keywords*: Bluetooth Low Energy (Ble), Person Detection, Indoor Localization, Smart Surveillance, Esp32, Apple Watch, Rssi, Ble Mesh, Privacy.*

I. INTRODUCTION

Bluetooth Low Energy (BLE) is a communication protocol designed to provide wireless connectivity at minimal power consumption. Since its inclusion in the Bluetooth 4.0 standard, BLE has become ubiquitous in smartphones, wearables, and IoT microcontrollers. Its energy efficiency and intermittent data exchange characteristics make it ideal for proximity-based services, including indoor localization and person detection.

Unlike GPS, which fails indoors due to signal attenuation, BLE offers reliable positioning by transmitting advertisement packets containing identity and metadata. These packets are received by BLE-capable devices, which measure the Received Signal Strength Indicator (RSSI). The simplicity of BLE infrastructure and the cost-effectiveness of beacons like iBeacon and ESP32 modules make BLE an attractive option for scalable deployments in smart buildings and homes.

II. BLE-BASED PERSON DETECTION METHODS

Bluetooth Low Energy (BLE) based person detection hinges on the idea that wireless signals degrade over distance. The Received Signal Strength Indicator (RSSI) serves as the core metric for estimating proximity and location. While simple in concept, RSSI-based localization is impacted by several environmental factors such as wall density, multipath interference, and body absorption. This section systematically explores signal modeling, classical detection methods, hybrid enhancements, and practical considerations for deployment.

A. RSSI Signal Modeling

The fundamental principle is based on radio frequency propagation where signal power decreases logarithmically with distance. The Log-Distance Path Loss Model is most commonly used:

$$RSSI(d) = RSSI_0 - 10n\log_{10}(d)$$

Where:

- $RSSI(d)$ is the signal strength at distance d (in meters)
- $RSSI_0$ is the RSSI at a reference distance (typically 1 meter)
- n is the path-loss exponent, which varies by environment (e.g., 2 in free space, up to 4 or more in complex indoor environments)

In practical applications, RSSI values are noisy. Techniques such as Kalman filtering, moving averages, or Gaussian noise modeling are used to mitigate volatility. Furthermore, packet loss and hardware variability across BLE devices introduce biases that need calibration.

B. Classical Localization Techniques

a) Proximity Detection

The simplest method is binary presence detection. If RSSI exceeds a threshold (e.g., -70 dBm), the person is deemed "present."

- Advantages: Easy to implement on mobile and embedded devices
- Limitations: Low spatial granularity, false positives due to signal fluctuations

Example**:** Smart lights that turn on when a BLE beacon (e.g., in a smartwatch) is nearby.

b) Trilateration

Trilateration uses estimated distances from three or more BLE beacons with known coordinates. The target's position is the intersection point of circles centered at each beacon.

$$(x - x_i)^2 + (y - y_i)^2 = d_i^2$$

Where $(x - x_i)^2$ is the beacon location, and d_i is the distance estimated from RSSI. The solution involves solving a system of nonlinear equations.

- Advantages: Geometrically intuitive and hardware-light
- Limitations: Highly sensitive to RSSI noise and beacon placement

Improvements**:** Employing least-squares optimization to reduce error when circles don't intersect perfectly due to noise.

c) Fingerprinting (Radio Map Matching)

Fingerprinting is a two-stage process:

i) Offline Phase:

The environment is surveyed, and RSSI values are collected at known grid locations to create a radio map (RSSI vectors).

ii) Online Phase:

Real-time RSSI vectors are matched to the database using classification algorithms like:

- k-NN (k-Nearest Neighbors)
- Support Vector Machines (SVM)
- Random Forests
- Artificial Neural Networks (ANNs)

iii) Advantages:

Higher accuracy in complex environments

iv) Limitations:

Labor-intensive setup and limited adaptability to dynamic layouts

Notable Work**:** Siu et al. demonstrated over 95% room-level accuracy using fingerprinting with BLE [1].

C. Signal Processing Enhancements

Due to RSSI instability, robust signal processing is vital:

Table 1 : Comparison of methods:

Method	Description	Usage Context
Moving Average	Smooths out short-term fluctuations	Lightweight, embedded devices
Kalman Filter	Predicts and updates RSSI state with noise model	Mobile robots, continuous tracking
Particle Filter	Probabilistic estimation using particle sets	Dynamic environments, high accuracy
Hidden Markov Model (HMM)	Models sequential transitions for state estimation	Human activity modeling

D. Hybrid Localization Approaches

BLE can be combined with other modalities to boost accuracy:

a) BLE + Ultrasonic

Used in systems like BLUESOUND, BLE is used for ID broadcast while ultrasonic sensors calculate precise distance using Time of Flight (ToF). This hybrid achieves <1 m accuracy even in crowded spaces.

b) BLE + Wi-Fi

Combining RSSI from BLE and Wi-Fi helps compensate for signal occlusion. BLE provides proximity, Wi-Fi provides fallback localization.

c) BLE + Inertial Sensors

Wearable IMUs (Inertial Measurement Units) track movement and direction. BLE beacons serve as checkpoints, while dead-reckoning fills in trajectory gaps.

E. Machine Learning in Detection

ML models enhance localization and person detection by learning signal patterns and environmental dynamics. Noteworthy models include:

- Convolutional Neural Networks (CNNs): RSSI vectors are interpreted as 1D images
- Recurrent Neural Networks (RNNs): Capture temporal changes in RSSI for trajectory prediction
- Autoencoders: Used for anomaly detection (e.g., identifying intrusions)

Deployment Note**:** Lightweight ML models can be run on edge devices like ESP32-S3, enabling near real-time person detection without reliance on cloud servers.

F. Accuracy Benchmarks

Table 2 : Benchmark Results

Method	Accuracy	Processing Cost	Hardware Needed
Proximity (RSSI threshold)	~3–5 meters	Low	Single beacon/receiver
Trilateration	~2–3 meters	Medium	≥3 beacons
Fingerprinting	~1–2 meters	High	Full radio map
BLE + Ultrasound	~0.3–1 meter	High	Ultrasound sensors
BLE + ML Filtering	~0.5–1.5 meters	Medium–High	Server or edge AI chip

G. Summary of Method Selection

The choice of method depends on:

- Environment type (open vs obstructed)
- Deployment scale (single room vs building-wide)
- Hardware cost constraints
- Required precision (e.g., room detection vs path tracking)
- Power budget (battery-powered sensors vs wall-powered nodes)

Hybrid and ML-based approaches generally offer better performance but come at the cost of complexity and compute power.

III. USE CASES IN REAL-WORLD APPLICATIONS

Bluetooth Low Energy (BLE)-based person detection systems are actively transforming a range of industries by enabling real-time indoor localization, identity-based automation, and context-aware surveillance. In this section, we discuss concrete use cases across healthcare, smart home systems, retail analytics, and building security.

A. Healthcare and Assisted Living

In hospitals and eldercare facilities, BLE person detection enhances patient safety and workflow efficiency. BLE tags worn by patients enable:

- Continuous localization in wards or dementia units.
- Fall detection using BLE 5.1's direction-finding capabilities.
- Geo-fencing, triggering alerts when a patient leaves a designated zone

Case Study: A 2022 study by Shahid et al. proposed a BLE-based fall detection and warning system specifically designed for nursing homes. It utilized directional BLE 5.1 signal analysis and smart tags for real-time monitoring [7].

B. Smart Homes and Ambient Automation

BLE enables personalized ambient control by recognizing which user is present and adapting home conditions accordingly:

- Lighting systems switch on/off based on proximity of BLE-tagged devices
- HVAC systems optimize energy usage using occupancy data
- Security systems arm/disarm based on resident movement

Implementation Example: ESP32 BLE scanners are deployed in rooms to detect residents carrying Apple Watches or smartphones. When a device is detected near the entrance, it triggers a Node-RED rule to disarm an alarm or unlock a smart door [8]

C. Surveillance and Intrusion Detection

BLE can be used for soft geofencing, enabling detection of:

- Unknown BLE devices (potential intruders)
- Missing known devices (e.g., lost wearable, stolen asset)
- Unauthorized entry or lingering in high-security areas

Example: The BLEDoorGuard system recognizes individuals by the pattern of their BLE signal signatures, enabling door access without RFID cards or biometrics [9].

D. Retail Analytics and Navigation

Retailers use BLE beacons to track foot traffic, monitor dwell times, and trigger location-based promotions on customer phones. BLE is also critical in indoor navigation for large shopping malls and public venues. [10]

IV. BLE MESH AND HYBRID SYSTEMS

A. BLE Mesh Networks for Large-Scale Person Detection

Traditional BLE operates in a star topology, where each peripheral communicates with a single central node. However, BLE Mesh, introduced in Bluetooth 5.0, enables many-to-many communications between nodes via message relaying. This architecture allows for:

- Scalability: Hundreds of nodes can monitor large facilities
- Redundancy: Mesh networks are resilient to individual node failure
- Distributed Control: Presence data can be processed locally before being aggregated

Use Case: In multi-room or multi-floor buildings, BLE Mesh supports continuous tracking of BLE-tagged individuals by relaying their signal data through intermediary nodes until it reaches the gateway [11].

B. Hybrid BLE Systems

Due to the inherent limitations of RSSI accuracy (typically ±3 meters), hybrid systems integrate BLE with other modalities:

a) BLE + Ultrasound

BLE is used for broadcasting identity while ultrasonic sensors estimate distance via Time of Flight (ToF). These hybrid setups achieve sub-meter accuracy, suitable for rooms with multiple occupants.

Example**:** The BLUESOUND system uses BLE to tag users and ultrasound arrays to determine their location within 30 cm accuracy [12].

b) BLE + Wi-Fi

BLE data is fused with Wi-Fi RSSI or MAC data to improve indoor coverage and accuracy in hybrid frameworks. Wi-Fi typically covers a broader range but lacks fine resolution.

c) BLE + Inertial Navigation

BLE provides location anchors, while IMU sensors (accelerometers, gyroscopes) enable dead reckoning between beacons. The combination is useful in scenarios requiring motion path reconstruction (e.g., evacuation tracking, warehouse robotics) [13].

C. Mesh and Hybrid System Challenges

The following table provide a summary view of the challenges between the two systems.

Table 3 : Summary view of challenges

Challenge	Description	Mitigation Strategy
Signal Congestion	BLE mesh introduces more nodes transmitting concurrently	Frequency hopping, adaptive routing
Privacy and Identity Spoofing	BLE signals are unencrypted by default	MAC randomization, encryption at higher layers
Calibration Drift	In hybrid systems, sensors can desynchronize	Time-stamped broadcasts and clock sync protocols
Hardware Cost	Ultrasound or UWB hardware increases system cost	Use BLE-only in non-critical zones

V. ARCHITECTURE OVERVIEW

Designing a BLE-based person detection system for indoor environments requires thoughtful integration of hardware, software, and network components. The architecture must support scalable signal acquisition, efficient data transmission, and robust decision-making at the edge or cloud. In this section, we present a typical BLE-based detection system architecture, its modular layers, and deployment patterns in real-world settings such as smart homes and health monitoring centers.

A. System Layers and Components

The overall architecture can be divided into four layers:

Table 4 : Layers in Architecture

Layer	Functionality	Technologies/Examples
Sensing Layer	Signal emission and acquisition	BLE tags (e.g., Apple Watch, iBeacon), ESP32
Network Layer	Data transmission and routing	BLE Mesh, Wi-Fi, MQTT, TCP/IP
Processing Layer	Signal filtering, positioning, pattern recognition	Kalman Filter, Trilateration, ML Models
Application Layer	Decision-making and user interaction (alerts, automation, logs)	Mobile app, dashboard, Node-RED, cloud APIs

B. End-to-End Workflow

a) Advertisement Broadcasting

BLE tags (e.g., iBeacons, smartwatches, or smartphones) periodically emit signals containing UUID, major/minor IDs, and power level (Tx).

b) *Signal* Reception

BLE scanners (e.g., ESP32, Raspberry Pi, smartphones) receive advertisements and extract RSSI values, timestamp, and device ID.

c) Data Transmission

The RSSI data is packaged (JSON, MQTT) and sent via Wi-Fi or BLE Mesh to a central edge gateway or cloud server.

d) Localization Estimation

Depending on system design:

- Edge devices may calculate proximity or zone detection
- Servers may execute trilateration, fingerprinting, or ML inference

e) Trigger Events

Based on rules or detection confidence, the system may:

- Unlock smart doors
- Send alerts to a mobile app
- Log movement patterns
- Adjust environmental controls (lights, HVAC)

C. Reference Implementation

Smart Room Setup Example:

- 3 BLE Beacons: Placed at known fixed locations (e.g., ceiling, desk, wall)
- BLE Scanners: ESP32s receive signals from wearables and report RSSI
- Wi-Fi Network: Used by ESP32 to publish MQTT messages to a broker
- Server Backend: Python + Flask + PostgreSQL database
- Processing: Implements trilateration, fingerprint lookup, and event triggering

D. Deployment Topologies

Table 5 : Deployment Topologies

Topology	Description	Use Case
Star	One central node (e.g., phone) receives from all beacons	Small office, entry monitoring
Mesh	Nodes relay messages across a distributed BLE network	Multi-floor hospitals, smart homes
Hybrid	BLE scanning with Wi-Fi or Ethernet backhaul for data reporting	Enterprise-scale buildings

E. Integration with Cloud and Edge AI

a) Modern BLE detection systems are increasingly hybridizing cloud and edge intelligence:

- Edge AI on ESP32-S3: Real-time decision making for critical applications (e.g., door unlock)
- Cloud AI (TensorFlow/ONNX): Long-term trend analysis, anomaly detection, behavior prediction

b) Benefits:

- Latency reduction
- Data privacy by limiting transmission
- Offline functionality in case of internet failure

F. Energy and Cost Considerations

BLE-based systems are optimized for battery longevity and hardware affordability:

- BLE Tags: Battery life of 6 months–2 years depending on interval
- ESP32 BLE Scanners: Cost <$5 per node; consume ~100–200mA during scanning
- Server: Can be a Raspberry Pi for small setups or a cloud VM for large deployments

G. Security Aspects

BLE communication by default is not encrypted. For secure deployments [14]:

- Use MAC randomization to protect user identity
- Pair BLE scanning with TLS over MQTT for backend communication
- Rotate UUIDs on a schedule to prevent tracking

H. BLE System Component Overview

Table 6 : BLE System Component Overview

Component	Function	Example Hardware	Notes
BLE Beacon	Signal broadcaster	Apple Watch, iBeacon	Transmit UUID and Tx power
BLE Scanner	RSSI data collection	ESP32, Raspberry Pi	Can be battery or mains powered
Gateway/Server	Data aggregation and processing	Node.js server, MQTT	Often includes security layer
Analytics Platform	Visualization, AI inference	Grafana, TensorFlow	Cloud-based or on-prem

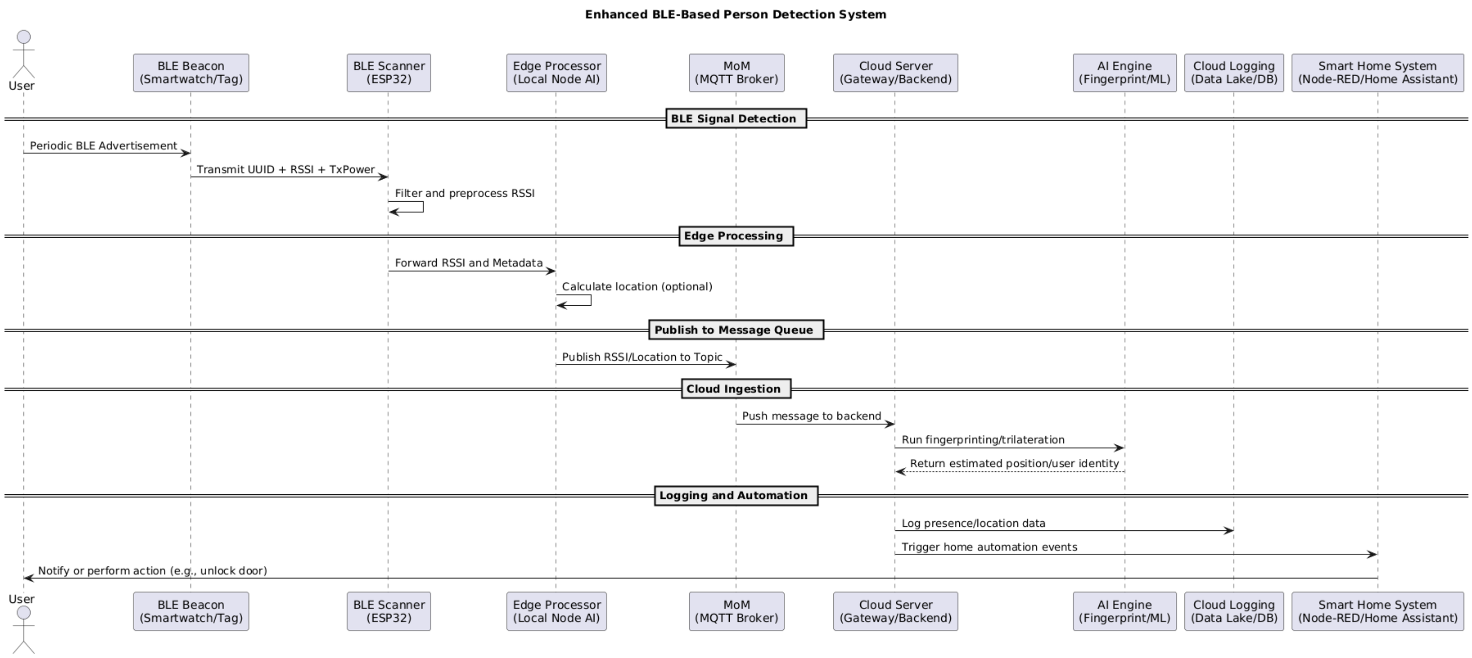

Figure 1 : Sequence diagram of BLE based person detection system

VI. CONCLUSION

Bluetooth Low Energy (BLE)-based person detection systems have gained traction across healthcare, smart home, and security sectors. However, their deployment is not without significant challenges. As systems scale and transition from prototypes to production-level implementations, limitations related to signal variability, scalability, privacy, and hardware inconsistencies have surfaced. Furthermore, as users become increasingly sensitive to surveillance technologies, regulatory and ethical considerations now play a critical role in shaping system design and deployment. This section outlines the most pressing technical and systemic challenges facing BLE-based person detection today, followed by a discussion of promising research directions that aim to mitigate these limitations.

One of the most fundamental technical issues in BLE localization is the instability of the Received Signal Strength Indicator (RSSI). BLE signals are susceptible to multipath propagation, human body absorption, and environmental interference. These factors introduce significant noise, making RSSI-based distance estimation inherently unreliable. In real-world settings, such as residential or hospital environments, the same beacon can exhibit RSSI fluctuations of up to 15 dBm depending on movement, wall structures, and even weather conditions. The result is often a localization error of several meters, rendering fine-grained positioning impractical without further signal smoothing techniques. Algorithms such as Kalman filtering or particle filters have been employed to mitigate this issue, but the problem remains a core limitation of RSSI-dependent systems.

Scalability is another key concern, especially in large deployments involving dozens or hundreds of BLE nodes. BLE operates in the crowded 2.4 GHz ISM band, shared with Wi-Fi and Zigbee. In high-density environments, BLE advertisement collisions can cause packet loss and channel congestion. These issues become particularly problematic in mesh topologies, where each node may relay messages to maintain network coverage. Without robust routing protocols and congestion mitigation strategies, the network can become saturated, undermining its real-time detection capability. Techniques such as adaptive beacon intervals, time-division multiplexing, and selective forwarding are being explored to address these bottlenecks.

Interoperability between BLE hardware platforms is also a significant hurdle. RSSI values vary substantially between different devices due to differences in antenna design, transmission power, and firmware calibration. For instance, an iPhone may report a significantly different RSSI value than an Android phone or an ESP32 module, even when receiving the same BLE advertisement. This variation complicates the deployment of standardized localization models across different hardware. Researchers have proposed calibration frameworks and normalization layers, but these solutions require additional setup and often lack generalizability. Moreover, software-level differences, such as how background BLE scanning is handled on Android vs. iOS, add another layer of complexity.

Security and privacy present additional challenges that are especially relevant in person-tracking applications. BLE was not originally designed with strong privacy mechanisms. By default, BLE beacons broadcast static MAC addresses and UUIDs, allowing for potential long-term tracking by malicious actors. Vulnerabilities such as spoofing, replay attacks, and man-in-the-middle exploitation are well-documented. Although newer versions of the BLE specification support MAC address randomization and encrypted payloads, many commercial devices and implementations do not enforce these features. Furthermore, when BLE-based systems are deployed in sensitive contexts such as hospitals or workplaces, compliance with regulations like GDPR, HIPAA, or CCPA becomes mandatory. These regulations require consent, transparency, and data minimization—conditions that are not trivial to satisfy in passive detection systems.

Despite these limitations, recent technological advancements are opening up new avenues for BLE-based person detection. One of the most promising directions is the integration of artificial intelligence to improve localization accuracy and system adaptability. Temporal models such as recurrent neural networks (RNNs) and long short-term memory (LSTM) architectures can learn from sequences of RSSI values, allowing the system to infer movement and transitions more reliably than static algorithms. Spatial models based on convolutional neural networks (CNNs) have also been used to interpret radio signal heatmaps for position classification. These models offer a substantial improvement in environments with frequent signal fluctuation, and transfer learning techniques are enabling pre-trained models to adapt to new physical layouts with minimal retraining.

Another breakthrough is the introduction of BLE 5.1 and its support for direction finding through Angle of Arrival (AoA) and Angle of Departure (AoD) estimation. Using antenna arrays and phase shift calculations, BLE 5.1 can localize devices with sub-meter accuracy. While hardware requirements for AoA (e.g., multi-element antennas) may limit its consumer adoption, enterprise and industrial settings are likely to benefit from its precision. AoA is particularly useful in scenarios requiring directional awareness, such as identifying the entry path of individuals in a smart building or monitoring movement patterns in a hospital.

As computing capabilities continue to shift toward the edge, federated learning and edge AI offer a new paradigm for BLE localization systems. Instead of transmitting raw data to the cloud, BLE scanners or edge gateways can perform inference locally, reducing bandwidth usage and enhancing privacy. Federated learning further allows devices to collaboratively update models without sharing raw data, aligning with privacy-by-design principles. This approach not only improves latency and efficiency but also addresses regulatory constraints by minimizing exposure of personally identifiable information (PII).

Multi-modal systems represent another forward-looking approach to overcoming BLE limitations. Hybrid platforms combine BLE with technologies such as Ultra-Wideband (UWB), Wi-Fi, inertial measurement units (IMUs), and ultrasound. BLE provides identity and coarse positioning, while UWB or ultrasound offers precision ranging. IMUs can track motion and orientation, enabling dead-reckoning between BLE beacons. Together, these technologies offer complementary strengths that surpass the capabilities of BLE alone. For instance, the BLUESOUND system integrates BLE with ultrasound to achieve sub-meter accuracy in tracking multiple residents in smart homes. These fusion systems are increasingly being applied to complex indoor environments such as airports, hospitals, and logistics warehouses.

Finally, BLE infrastructure is being extended beyond buildings into smart cities. Public infrastructure such as lamp posts, bus stations, and transportation hubs are embedding BLE beacons to passively detect crowd movement, optimize transit schedules, and enhance urban security. While such systems raise additional ethical questions about surveillance and data ownership, they demonstrate the broad potential of BLE as a ubiquitous layer in future sensing environments.

In summary, while BLE-based person detection systems face critical challenges around signal quality, scalability, hardware diversity, and privacy, these are being addressed through a confluence of innovations in wireless technology, machine learning, and edge computing. Future BLE systems will likely be smarter, more secure, and better integrated with other sensing modalities, making them foundational components in the next generation of intelligent spaces

Interest Conflicts

The author declares that there is no conflict of interest concerning the publishing of this paper.

VII. REFERENCES

[1] Atzori, L., Iera, A., & Morabito, G. (2010). The Internet of Things: A survey. *Computer Networks*, 54(15), 2787–2805.

[2] Al-Fuqaha, A., Guizani, M., Mohammadi, M., Aledhari, M., & Ayyash, M. (2015). Internet of Things: A survey on enabling technologies, protocols, and applications. *IEEE Communications Surveys & Tutorials*, 17(4), 2347–2376.

[3] Bonomi, F., Milito, R., Zhu, J., & Addepalli, S. (2012). Fog computing and its role in the Internet of Things. *Proceedings of the First Edition of the MCC Workshop on Mobile Cloud Computing*, 13-16.

[4] Centenaro, M., Vangelista, L., Zanella, A., & Zorzi, M. (2016). Long-range communications in unlicensed bands: The rising stars in the IoT and smart city scenarios. *IEEE Wireless Communications*, 23(5), 60-67.

[5] Dorri, A., Kanhere, S. S., Jurdak, R., & Gauravaram, P. (2017). Blockchain for IoT security and privacy: The case study of a smart home. *IEEE PerCom Workshops*, 618-623.

[6] Gubbi, J., Buyya, R., Marusic, S., & Palaniswami, M. (2013). Internet of Things (IoT): A vision, architectural elements, and future directions. *Future Generation Computer Systems*, 29(7), 1645-1660.

[7] Shahid, N. De Raeve, M. De Schepper, (2022)., "Bluetooth-Low-Energy-Based Fall Detection and Warning System for Elderly People in Nursing Homes," Journal of Ambient Intelligence and Humanized Computing, 2022. DOI:10.1155/2022/9930681

[8] M. Collotta and G. Pau, (2015) "A Solution Based on Bluetooth Low Energy for Smart Home Energy Management," Energies, vol. 8, no. 10, pp. 11916–11938, 2015. DOI:10.3390/en81011916

[9] W. Shao, T. Nguyen, K. Qin, and M. Youssef, (2018) "BLEDoorGuard: A Device-Free Person Identification Framework Using Bluetooth Signals for Door Access," IEEE Internet of Things Journal, vol. 5, no. 3, pp. 2171–2184, 2018. DOI:10.1109/JIOT.2018.2825959

[10] R. Faragher and R. Harle,(2015) "Location Fingerprinting With Bluetooth Low Energy Beacons," IEEE Journal on Selected Areas in Communications, vol. 33, no. 11, pp. 2418–2428, Nov. 2015. DOI:10.1109/JSAC.2015.2430281

[11] M. R. Ghori, T. C. Wan, and G. C. Sodhy, (2020) "Bluetooth Low Energy Mesh Networks: Survey of Communication and Security Protocols," Sensors, vol. 20, no. 12, p. 3590, 2020. DOI:10.3390/s20123590

[12] G. Mokhtari, Q. Zhang, G. Nourbakhsh, and S. Ball, (2017) "BLUESOUND: A New Resident Identification Sensor Using Ultrasound Array and BLE Technology for Smart Home Platform," IEEE Sensors Journal, vol. 17, no. 12, pp. 3721–3732, 2017. DOI:10.1109/JSEN.2017.2702339

[13] P. Davidson and R. Piché, (2017) "A Survey of Selected Indoor Positioning Methods for Smartphones," IEEE Communications Surveys & Tutorials, vol. 19, no. 2, pp. 1347–1370, 2017. DOI:10.1109/COMST.2016.2632427

[14] R. Rios and J. Hoang, (2020) "Security Vulnerabilities in BLE: A Survey," International Journal of Network Security, vol. 22, no. 3, pp. 420–430, 2020.