A BIM-Driven Hybrid Wi-Fi/BLE Indoor Positioning Framework for Real-Time 3D Localization and Digital Twin Development

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Abstract

Developing functional digital twins for smart buildings requires accurate, real-time indoor localization tightly linked to the building’s spatial and semantic structure. However, most Indoor Positioning Systems (IPS) lack integration with Building Information Modeling (BIM), which limits 3D visualization and synchronized spatial management. This study proposes a BIM-driven hybrid localization framework that combines Wi-Fi and Bluetooth Low Energy (BLE) Received Signal Strength (RSS) data with BIM to create a unified data foundation for real-time 3D indoor positioning. The experimental system was implemented on the fourth floor of the Faculty of Geography at the University of Tehran, where a BIM model provided geometric and semantic references (IfcSpace, IfcStorey). RSS measurements from 35 reference points and seven transmitters were processed using two models: (1) Fingerprinting, implemented with a Multilayer Perceptron (MLP), and (2) Trilateration, based on a log-distance path-loss model. While Fingerprinting achieved high spatial accuracy (RMSE ≈ 0.40 m) and Trilateration showed larger positioning deviations (RMSE ≈ 2.38 m), a hybrid adaptive weighting strategy combined their outputs to obtain over 95% accuracy within one meter. The results confirm that BIM linkage enhances both positional precision and semantic consistency, enabling accurate mapping of user trajectories within a 3D building environment. The system operates through a three-tier workflow consisting of a mobile client, processing server, and BIM visualization layer, utilizing IFC and GeoJSON data formats. This framework provides a scalable foundation for digital-twin applications, with future extensions anticipated in multi-floor tracking, IoT data integration, emergency routing, and occupant flow analysis.

1.Introduction

In the era of smart cities, accurately localizing people, assets, and equipment within indoor spaces forms the foundation for intelligent facility management, spatial analytics, and context-aware services. While Global Positioning Systems (GPS) perform reliably outdoors, their signals degrade severely in indoor environments due to attenuation, obstruction, and multipath propagation (Al Nuaimi & Kamel, 2011; Gu et al., 2009). Consequently, the development of high-accuracy, cost-effective, and scalable Indoor Positioning Systems (IPS) has become a major research focus in geoinformatics and spatial information science (Qi et al., 2024).

A wide range of technologies—including Wi-Fi, Bluetooth Low Energy (BLE), Ultra-Wideband (UWB), ZigBee, and vision-based systems—have been explored for indoor localization (Hightower & Borriello, 2001; Mautz, 2012). Among these, Fingerprinting and Trilateration remain the most widely adopted due to their favorable balance between accuracy, computational simplicity, and implementation cost (Farid et al., 2013; Haznedar et al., 2023). The Fingerprinting approach, which relies on Received Signal Strength (RSS) patterns collected from reference points, can achieve high spatial accuracy but is sensitive to environmental changes and requires frequent database updates (Abdullah et al., 2023). In contrast, the Trilateration approach estimates positions based on signal power decay models; while computationally efficient, it performs poorly in complex indoor settings where multipath and non-line-of-sight (NLOS) effects distort distance estimations, leading to large positioning errors (Bai et al., 2023).

To mitigate these limitations, recent research has introduced hybrid localization techniques that combine multiple technologies and algorithms to improve both accuracy and robustness. Integrating Wi-Fi and BLE signals provides a complementary solution: Wi-Fi offers wider coverage, whereas BLE achieves higher precision at short ranges (Luo & Chen, 2019; Haznedar et al., 2023). However, most hybrid systems focus primarily on algorithmic optimization rather than structured spatial integration with Building Information Modeling (BIM). As a result, they often lack true 3D spatial representation and real-time update capabilities (Kakisim & Turgut, 2025; Sonny et al., 2024).

Building Information Modeling provides both semantic and geometric foundations for managing a building’s lifecycle, enabling standardized representation of spaces and elements through the Industry Foundation Classes (IFC) schema—such as IfcSpace and IfcStorey (Alitaleshi et al., 2023). Linking IPS data to BIM allows dynamic movements of occupants to be represented in a three-dimensional digital environment, thereby establishing the foundation for a Digital Twin—an integrated system in which physical and virtual spaces continuously exchange data (Broz et al., 2025).

In this context, the present study proposes a BIM-driven hybrid localization framework that bridges sensor-based signal data and model-based spatial information. Wi-Fi and BLE RSS measurements are simultaneously collected and processed using Fingerprinting and Trilateration algorithms, whose outputs are

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adaptively fused and linked to BIM entities (IfcSpace, IfcStorey) for real-time 3D visualization of user positions.

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2.Study Area and Data

The experimental dataset was collected on the fourth floor of the Faculty of Geography at the University of Tehran—a complex educational environment comprising classrooms, offices, narrow corridors, and open spaces separated by thick plaster walls. This configuration, characterized by reflective surfaces and multiple physical obstacles, created realistic signal propagation challenges such as multipath effects and attenuation, making it an ideal testbed for evaluating indoor positioning accuracy (Haznedar et al., 2023; Luo & Chen, 2019).

A three-dimensional BIM model of the floor was reconstructed in Autodesk Revit with a Level of Detail (LOD) of 100–200, representing both structural components (walls, ceilings, doors) and spatial features (*IfcSpace*, *IfcStorey*). The model was georeferenced to UTM Zone 39N, enabling seamless integration of geometric and spatial data into a BIM-driven database. Each reference point (RP) was associated with its corresponding *IfcSpaceID*, storey, and elevation, ensuring that spatial and signal attributes could be linked consistently within the same coordinate framework (Alitaleshi et al., 2023; Qi et al., 2024).

Four Wi-Fi access points and three BLE beacons were strategically deployed to guarantee that every RP was covered by at least three to five transmitters, thereby minimizing potential signal blind zones (Varshney et al., 2017).

Figure 1 illustrates the three-dimensional BIM model of the Faculty of Geography building and the deployment of Wi-Fi access points, BLE beacons, and reference points (RPs) on the fourth floor. Panel (a) shows the exterior view of the main building, while panel (b) presents the Revit-based 3D reconstruction with transmitter and RP locations, including a legend distinguishing signal types. As shown in the figure, the BIM model served not only as a geometric representation but also as an informational structure in which each building element possessed a unique IFC identifier. This structure enabled direct linkage between signal data and spatial entities, forming the foundation of the BIM-based radiometric map used in this study.

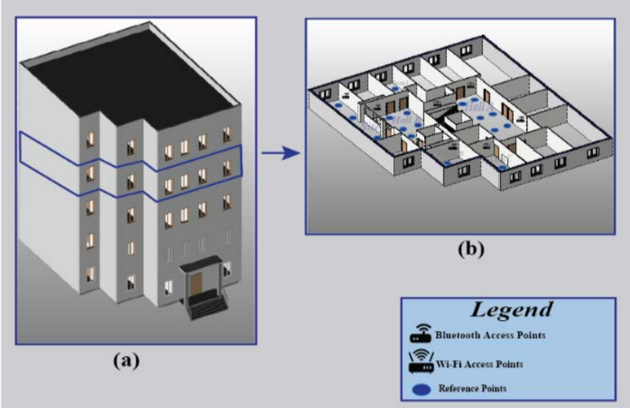

Figure 1. Three-dimensional BIM model of the Geography Faculty building and deployment of Wi-Fi access points, BLE beacons, and reference points (RPs) on the fourth floor: (a) exterior view of the main building; (b) Revit-based 3D reconstruction showing transmitter and RP locations with legend indicating signal types.

For data acquisition, 35 reference points were distributed approximately every two meters. At each RP, Received Signal Strength (RSS) values from the four Wi-Fi access points and three BLE beacons were recorded using a custom Android application that simultaneously scanned all transmitters and exported the readings in CSV format. Multiple samples were averaged to mitigate noise, filtered using the Interquartile Range (IQR) method, and normalized via min–max scaling to standardize signal ranges (Abdullah et al., 2023; Fedosova et al., 2021).

The processed measurements were organized into a BIM-driven Fingerprint Dataset that connected signal data with geometric and semantic information derived from the Revit model. Table 1 summarizes the structure of this integrated dataset, which includes four primary components: Wi-Fi RSS values collected from access points, BLE RSS values recorded from beacons, 3D coordinates of each reference point derived from the BIM model, and BIM elements such as *IfcSpaceID* and *IfcStorey* used for semantic linkage. This unified data schema establishes a direct connection between radiometric observations and building geometry, enabling precise three-dimensional localization and BIM-based spatial analysis (Luo & Chen, 2019).

Data Type	Description	Source /Tool	Format	Key Fields
Wi-Fi RSS	Four access point signal strengths	Android app	CSV	ID, RSS1–RSS4, Timestamp
BLE RSS	Three beacon signal strengths	Same app	CSV	RSS_B1–RSS_B3
Coordinates	RP position (X, Y, Z)	Manual survey / BIM	GeoJSON	X, Y, Z

Data Type	Description	Source /Tool	Format	Key Fields
BIM Elements	Space, storey, geometric ID	Revit (IFC export)	IFC	IfcSpaceID, IfcStorey

Table 1. BIM-driven Fingerprint Dataset Schema

All datasets were unified under UTM Zone 39N**,** ensuring that each RP contained both signal and spatial attributes—space, elevation, and floor—within a multilayered dataset suitable for precise 3D analysis (Rajab & Wang, 2024). During data acquisition, realistic indoor conditions were maintained: people moved, doors opened and closed, and reflective surfaces such as ceramic floors generated multipath effects. Wi-Fi signal strengths ranged from −45 to −80 dB, while BLE signals ranged from −60 to −90 dB, representing realistic levels of variability in indoor environments (Haznedar et al., 2023; Wang & Ahmad, 2025).

3.Methodology

This study aims to design and implement a hybrid indoor positioning system based on Wi-Fi and Bluetooth Low Energy (BLE) signals and to integrate it with a Building Information Model (BIM) as a foundation for developing digital twins of smart buildings. The proposed framework performs all stages—from signal acquisition in the physical environment to real-time visualization within the BIM model—through an automated, data-driven workflow. The system follows a three-tier architecture comprising (i) a mobile-client layer for signal collection, (ii) a processing server for model computation, and (iii) a BIM layer for spatial integration and visualization (Haznedar et al., 2023; Alitaleshi et al., 2023).

In the mobile layer, a custom Android application continuously collects Wi-Fi and BLE Received Signal Strength (RSS) values and transmits them to the server. Within the server layer, the data are normalized and processed in parallel using two models: Fingerprinting, which learns RSS spatial patterns through a Multilayer Perceptron (MLP), and Trilateration, which estimates user distance from transmitters via the log-distance path-loss model. Finally, in the BIM layer, the outputs of both models are combined using a dynamically weighted hybrid approach that balances accuracy and stability (Luo & Chen, 2019; Qi et al., 2024).

Figures 2 and 3 together illustrate the complete methodological workflow and operational data flow of the proposed BIM-driven hybrid indoor positioning framework. As shown in Figure 2, the process begins with the preparation of a base map in the BIM environment, where control points are established and the spatial reference of the study area is defined. Subsequently, Wi-Fi and BLE transmitters are strategically deployed throughout the environment, and initial RSS data are collected to capture signal characteristics under realistic indoor conditions. These measurements form the foundation for the development of the Fingerprinting model, which constructs a radiometric map representing spatial signal distributions and learns nonlinear RSS–location relationships using an MLP network. Parallel to this, a Trilateration-based model is implemented to estimate user positions geometrically based on RSS-derived distances from reference points. Once both sub-models reach acceptable accuracy thresholds—less than 3 m error for Trilateration and above 80 % accuracy for Fingerprinting—their outputs are combined through an adaptive weighting process to create a hybrid estimation of user position. The final step involves implementing the hybrid model within a mobile application and linking its results to the BIM model for three-dimensional visualization and real-time monitoring. In addition to visualization, BIM entities (IfcSpace and IfcStorey) were used as semantic constraints to verify spatial consistency and eliminate physically implausible localization results across adjacent rooms and floors. This integrated workflow ensures continuous accuracy improvement, stability, and scalability from signal acquisition to BIM-based digital-twin representation.

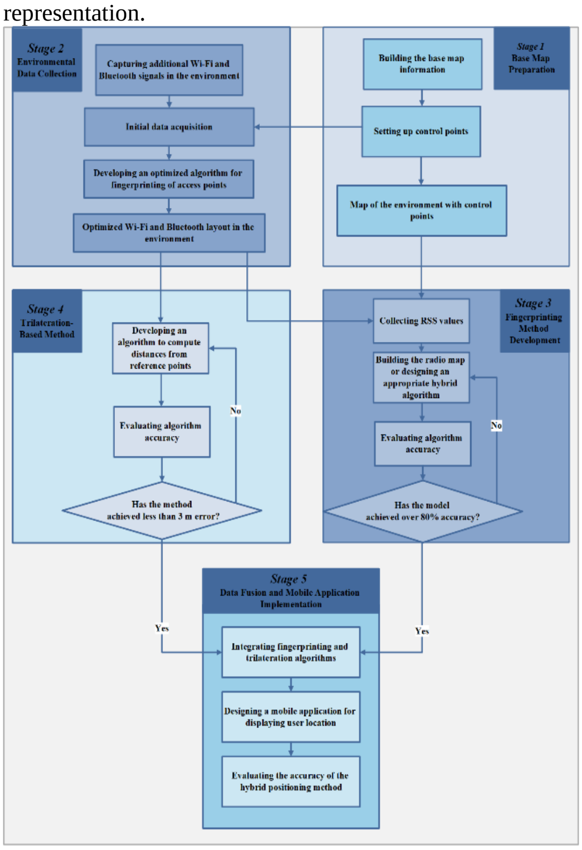

Figure 2. Overall methodological workflow of the proposed BIM-driven hybrid indoor positioning system.

Figure 3 further illustrates the dynamic interaction among the mobile application, the processing server, and the BIM environment during real-time operation. When a user initiates a localization request, the mobile application scans surrounding Wi-Fi Access Points and BLE beacons to collect RSS measurements and transmits them to the server. The server then performs data normalization and pre-processing, selects the top-k candidate positions using the Fingerprinting model, and computes geometric distances through the Trilateration model. The hybrid fusion algorithm combines both outputs to determine the final position, which is subsequently sent back to the mobile application and simultaneously synchronized with the BIM model. Within the BIM environment, the estimated position is visualized as a dynamic point associated with its corresponding

IfcSpace and IfcStorey elements, ensuring semantic and geometric consistency between physical and virtual spaces.

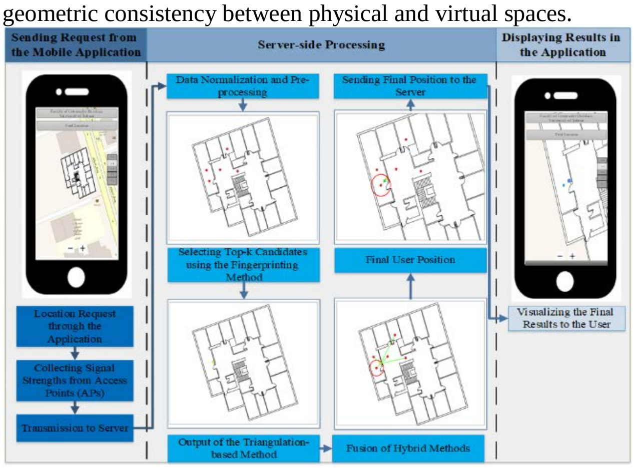

Figure 3. Step-by-step data flow between the mobile application, server, and BIM model in the hybrid localization system.

In the Trilateration model, the distance *d* between a user and an access point is derived as:

$$d = 10^{\frac{(RSS_0 - RSS)}{10n}} \quad (1)$$

where RSS_0 is the reference signal strength, n is the path-loss exponent, and d represents the estimated distance. The final position is calculated using the Weighted Least Squares (WLS) method (Luo & Chen, 2019). To achieve a stable hybrid estimation, the results of the two sub-models are fused according to:

$$P_{final} = w_f \times P_{fingerprint} + (1 - w_f) \times P_{trilateration} \quad (2)$$

where P_{final} is the predicted position and w_f is the weighting factor assigned to the fingerprinting model. The optimal w_f was empirically determined to balance spatial precision and temporal robustness (Haznedar et al., 2023; Kakisim & Turgut, 2025).

During system deployment, the experiments were conducted on the fourth floor of the Faculty of Geography to maintain controlled indoor conditions. Although the current version of the mobile application provides 2D visualization for that floor, both the conceptual framework and the BIM database were developed in 3D, ensuring scalability to multi-storey digital-twin environments. In the final integration phase, the predicted coordinates were linked to BIM entities (IfcSpaceID, IfcStoreyElevation) and displayed as dynamic points in Autodesk Revit, forming a live digital-twin representation (Broz et al., 2025).

Table 2 summarizes the three localization approaches implemented in this study, including their input technologies, core algorithms, technical characteristics, and primary advantages. The comparison highlights the complementary strengths of the Fingerprinting, Trilateration, and Hybrid models within the proposed BIM-driven localization framework.

Model	Input Technology	Core Algorithm	Technical Feature	Main Advantage
Fingerprinting (MLP)	Wi-Fi + BLE	Multilayer perceptron (ReLU)	Learns RSS spatial patterns	High accuracy in complex environments
Trilateration	Wi-Fi + BLE	Path loss model + WLS	Distance estimation from RSS	Computational simplicity
Hybrid	Combination of both	Dynamic weighted averaging	Balanced accuracy–stability trade-off	Real-time and robust performance

Table 2. Summary of localization models and their key characteristics

4.Results and Evaluation

To evaluate the performance of the proposed BIM-driven hybrid indoor positioning framework, several experiments were conducted under real conditions on the fourth floor of the Faculty of Geography building at the University of Tehran. The test area consisted of classrooms, offices, and narrow corridors separated by thick plaster walls, creating strong multipath reflections and attenuation zones. These environmental complexities made the site an ideal benchmark for assessing the reliability and robustness of signal-based localization methods. During data collection, normal indoor activities—such as people walking and doors opening and closing—were allowed to simulate realistic environmental dynamics. The main objective was to compare the performance of the Fingerprinting, Trilateration, and Hybrid models, and to evaluate the contribution of BIM integration to improving spatial precision and stability (Qi et al., 2024; Haznedar et al., 2023; Luo & Chen, 2019).

4.1 Fingerprinting Model

The Fingerprinting model, implemented using a Multilayer Perceptron (MLP), was trained on RSS vectors collected from seven transmitters (four Wi-Fi access points and three BLE beacons). The model successfully captured complex nonlinear relationships between signal strength and spatial position, producing stable and highly accurate predictions. It achieved an average Root Mean Square Error (RMSE) of 0.37–0.40 m and a Mean Absolute Error (MAE) of 0.21 m, with more than 95% of estimates falling within one meter of the true position.

Figure 4 illustrates the distribution of localization errors across all 35 reference points (RPs). Each color bar represents the average error for one access point at a specific RP. Error values remained consistently low, typically below 1 m, with only minor spikes observed near thick wall sections or the elevator area—locations prone to strong multipath effects. These results confirm the strong spatial learning capability of the MLP-based Fingerprinting model, which maintained high precision even under variable signal conditions. The narrow, uniformly distributed bars in the figure indicate excellent model generalization and stable indoor performance comparable to state-of-the-art IPS methods (Alitaleshi et al., 2023; Abdullah et al., 2023).

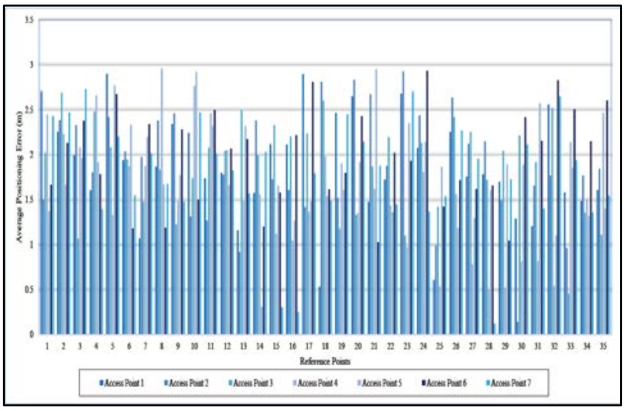

Figure 4. Distribution of localization error for the fingerprinting model (x-axis: error in meters; y-axis: number of RPs).

4.2 Trilateration Model

The Trilateration model was implemented using the Log-Distance Path Loss (LDPL) equation and solved through the Weighted Least Squares (WLS) algorithm. While computationally efficient and conceptually simple, the model proved highly sensitive to signal noise and non-line-of-sight (NLOS) conditions.
Figure 5 presents a histogram of mean positioning errors for all RPs. The distribution ranged between 0.5 m and 3.5 m, with most errors concentrated around 2 m. This pattern highlights the instability of distance-based localization in environments with severe multipath interference. RPs near walls, metal structures, or corners exhibited the largest deviations due to signal distortion, whereas those with direct line-of-sight to multiple transmitters achieved smaller errors. The findings underline the limitations of purely geometric approaches and reinforce the need for hybrid integration to mitigate the effects of multipath and attenuation (Gu et al., 2009; Bai et al., 2023).

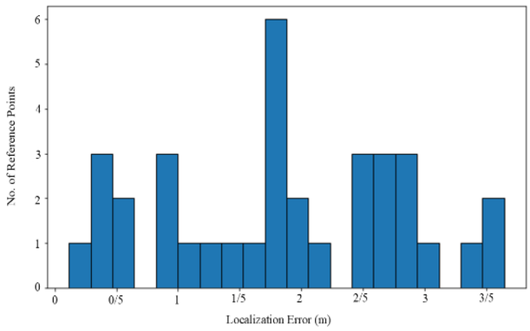

Figure 5. Mean positioning error of the trilateration model for each RP and transmitter (Wi-Fi/BLE).

4.3 Hybrid Model and Comparative Analysis

To address the limitations of the individual methods, the hybrid framework fused the outputs of the Fingerprinting and Trilateration models using the adaptive weighting mechanism described in Section 3. The weighting factor wfw_fwf dynamically adjusted the contribution of each sub-model based on signal stability and spatial context.
Table 3 summarizes the statistical results. The hybrid model achieved sub-meter accuracy comparable to Fingerprinting (RMSE ≈ 0.40 m) while providing greater temporal robustness and smoother trajectory continuity. It combined the fine spatial precision of Fingerprinting with the geometric consistency of Trilateration, yielding 95% accuracy within one meter even under variable indoor conditions. This balanced performance demonstrates that the hybrid approach effectively mitigates short-term RSS fluctuations while preserving spatial fidelity, resulting in a stable and continuous user trajectory (Haznedar et al., 2023; Kakisim & Turgut, 2025). While the Fingerprinting model achieves the lowest point-wise localization error, the primary motivation for hybrid integration is not solely numerical accuracy but robustness and temporal stability. The hybrid model maintains sub-meter accuracy comparable to Fingerprinting while reducing short-term fluctuations and improving trajectory smoothness under dynamic indoor conditions. This behavior is particularly important for real-time digital twin applications, where stable and continuous positioning is often more critical than marginal improvements in instantaneous accuracy.

Model	Input	RMSE	MAE	Error < 1 m	Remarks
		m	m	%	
Fingerprinting (MLP)	Wi-Fi + BLE	0.40	0.21	95%	High accuracy and good stability
Trilateration (WLS)	Wi-Fi + BLE	2.38	1.67	42%	Sensitive to multipath and attenuation
Hybrid (Weighted Fusion)	Wi-Fi + BLE	0.40	0.26	95%	Balanced accuracy, stability, and responsiveness

Table 3. Statistical comparison of localization models

4.4 Spatial Visualization and BIM Validation

The integration of localization results with BIM substantially enhanced spatial interpretation and model validation. **Figure 6** shows the three-dimensional alignment between true (light blue) and predicted (dark blue) user positions inside the BIM model of the fourth floor. Each estimated point was automatically mapped to its corresponding IfcSpace (room) and IfcStorey (floor level), ensuring semantic consistency between sensor-based and model-based datasets.
Visual inspection indicates that nearly all predicted positions fall within the correct room boundaries, with deviations below 0.5 m. This confirms that geometric integration with BIM effectively compensates for minor signal errors. The close spatial correspondence between true and estimated positions demonstrates real-time synchronization between physical and digital environments—forming the foundation for a live digital

twin capable of supporting real-time asset tracking, occupancy monitoring, and emergency route optimization (Broz et al., 2025).

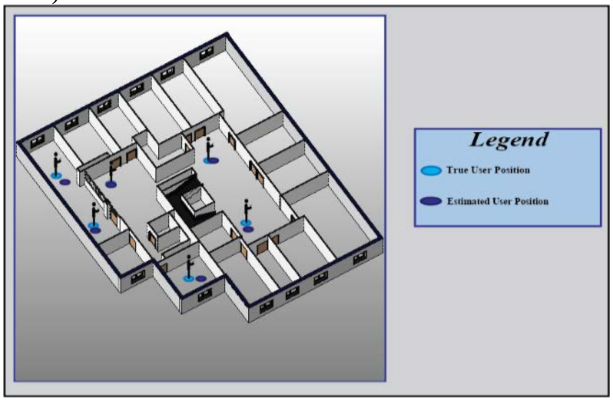

Figure 6. Spatial alignment between true (light blue) and predicted (dark blue) user positions within the 3D BIM model (Legend: True vs. Estimated).

4.5 Role of BIM Data in Accuracy Enhancement

Incorporating BIM spatial parameters—particularly the vertical (Z) dimension and IfcSpace boundaries—significantly improved the system’s ability to differentiate between vertically and horizontally adjacent rooms. By enforcing geometric constraints derived from the BIM structure, the framework reduced the effects of wall and ceiling attenuation and enhanced the separability of RSS patterns. Even when signal intensities were similar between rooms, the spatial logic encoded in BIM allowed correct positional assignment. Consequently, temporal consistency improved, and false room transitions were minimized (Luo & Chen, 2019; Qi et al., 2024).

4.6 System Response Time and Computational Efficiency

System performance was further analyzed to assess real-time responsiveness. A total of 100 consecutive localization requests were executed on a workstation equipped with an Intel Core i7 (2.8 GHz), 16 GB RAM, and Windows 10. Each request involved three main computational steps: (1) RSS preprocessing and Fingerprinting inference, (2) distance estimation using Trilateration, and (3) hybrid fusion followed by BIM visualization.

Table 4 lists the average processing time of each component. The overall response time was approximately 0.274 seconds, confirming near real-time operation. Figure 7 presents the response time distribution across all 100 localization requests. The hybrid method (shown in dark blue) required slightly more time than individual models due to fusion operations but consistently maintained execution below 0.3 seconds per request. The Fingerprinting component accounted for roughly 30% of total time, Trilateration for 10%, and hybrid fusion for 60%, while BIM visualization introduced less than 10% overhead. The linear response trend indicates that the proposed system can efficiently support multi-user, real-time localization without perceptible delay, confirming its suitability for operational smart-building applications (Rajab & Wang, 2024).

Component	Average Time	Share of Total
	s	%
Fingerprinting (MLP)	0.082	30
Trilateration (WLS)	0.027	10
Hybrid Fusion	0.165	60
BIM Visualization	0.027	<10
Total Response Time	0.274	100

Table 4. Processing time of system components

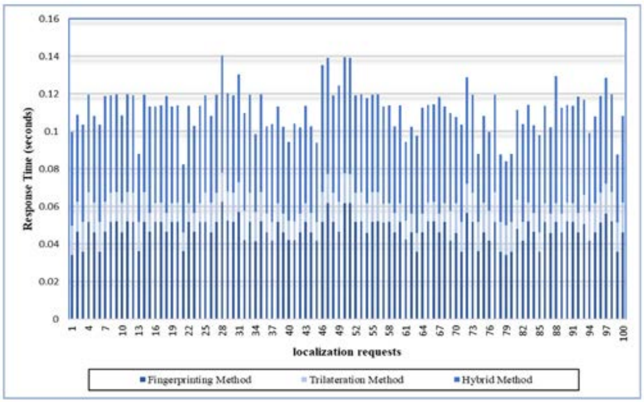

Figure 7. Response time of 100 consecutive localization requests for the three models.

In summary, the experimental evaluation demonstrates that integrating signal-based models with BIM yields high positioning accuracy (RMSE ≈ 0.4 m), low response time (≈ 0.27 s), and robust real-time visualization within a three-dimensional digital-twin environment. Collectively, the results presented in Figures 4–7 and Tables 3–4 confirm that the proposed BIM-driven hybrid Wi-Fi/BLE localization framework provides a reliable, scalable, and practical solution for next-generation smart-building tracking and management.

5. Discussion and Conclusion

The findings of this study demonstrate that integrating hybrid Wi-Fi and BLE signal data with the geometric and spatial information of a Building Information Model (BIM) can significantly enhance both the accuracy and temporal stability of indoor positioning systems. By combining the strengths of the Fingerprinting and Trilateration methods, the proposed framework effectively modeled nonlinear signal attenuation patterns through a Multilayer Perceptron (MLP) and dynamically fused the outputs of both models. This fusion reduced the overall positioning error to approximately 0.4 m, achieving sub-meter accuracy suitable for real-time indoor applications such as smart navigation, occupancy monitoring, and asset tracking (Haznedar et al., 2023; Qi et al., 2024).

Although BIM is visually represented in the proposed framework, its role extends beyond simple floor-map visualization. BIM provides structured semantic and geometric constraints—such as IfcSpace boundaries, storey elevation, and room topology—that are explicitly used to validate and correct localization outputs. Unlike a 2D floor plan, BIM enables three-dimensional spatial reasoning, vertical differentiation, and semantic consistency between estimated positions and actual building spaces. This integration reduces cross-room ambiguity and constrains unrealistic transitions caused by signal noise, thereby enhancing positional stability and digital-twin readiness rather than merely serving as a visualization layer.

Compared to conventional Trilateration approaches, the hybrid model exhibited superior robustness against signal noise and environmental variability. The adaptive weighting mechanism efficiently balanced the contributions of the two sub-models, maintaining spatial stability even under multipath and obstruction-prone conditions. Moreover, directly linking the localization outputs to BIM entities—*IfcSpace* and *IfcStorey*—ensured geometric consistency between estimated positions and building structure. This integration not only enabled accurate 3D visualization of user locations but also allowed the system to recognize physical room boundaries, thereby reducing cross-room interference and reflection-induced errors (Luo & Chen, 2019; Alitaleshi et al., 2023).

Within this framework, the BIM model functioned as more than a geometric reference; it served as a real-time digital backbone connecting physical and virtual environments. The linkage of live positioning data to BIM established a dynamic digital twin, where spatial changes in the physical space were continuously mirrored in the digital model (Broz et al., 2025). This capability provides a foundation for intelligent building management systems, including energy monitoring, access control, and emergency evacuation planning. The integration of the vertical (Z) dimension further enhanced 3D analytical capability, representing a crucial step toward multi-storey digital twin development (Rajab & Wang, 2024).

From a computational perspective, the entire workflow—from RSS data acquisition to 3D visualization within the BIM environment—was executed in an average of 0.275 seconds, confirming near real-time performance. The use of a Python-based API for Autodesk Revit enabled seamless communication between the processing server and BIM model with minimal computational overhead, allowing user positions to be visualized almost instantaneously. This responsiveness is essential for time-critical indoor applications such as live navigation and asset tracking (Kakisim & Turgut, 2025).

When compared with related studies, the proposed hybrid framework demonstrated notably higher accuracy. Previous research has shown that conventional Wi-Fi- or BLE-based methods typically achieve localization errors of 1–2 m (Li et al., 2024; Sun et al., 2023; Chen et al., 2025), whereas the present BIM-driven approach achieved sub-meter precision of approximately 0.4 m. These results confirm the potential of BIM-integrated localization for bridging the gap between sensor-based IPS solutions and model-based digital environments, offering a scalable blueprint for the digital infrastructure of smart buildings both in Iran and internationally.

Despite these promising results, certain limitations remain. The experimental setup was restricted to a single floor, and future studies should extend the framework to multi-storey buildings and analyze vertical signal propagation. In addition, the dataset was collected over a limited time span; therefore, long-term monitoring is recommended to evaluate temporal drift and signal stability. Integrating IoT sensor data—such as temperature, humidity, and motion—could transform the system from a spatial digital twin into a functional one. Furthermore, advanced deep-learning architectures, including CNN–LSTM networks, Graph Neural Networks (GNNs), or Transformers, could be employed to enhance the temporal modeling of RSS dynamics. Finally, the development of BIM-based analytical dashboards for crowd management, emergency routing, and energy optimization would support broader real-world deployment (Rajab & Wang, 2024; Kakisim & Turgut, 2025).

In conclusion, this research has demonstrated that a BIM-driven hybrid Wi-Fi/BLE localization framework can achieve sub-meter accuracy while maintaining real-time responsiveness. The direct linkage of hybrid model outputs to IFC entities enables dynamic visualization, spatial analysis, and user tracking within a unified 3D BIM environment. This approach provides a robust foundation for the future development of digital twins in smart buildings, paving the way for the integration of GeoAI, IoT, and spatial deep-learning technologies in intelligent indoor management systems.

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