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REVIEW ARTICLE

Advancing indoor positioning systems: innovations, challenges, and applications in mobile robotics

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Abstract
Indoor positioning systems (IPS) are essential for mobile robot navigation in environments where global positioning systems (GPS) are unavailable, such as hospitals, warehouses, and intelligent infrastructure. While current surveys may limit themselves to specific technologies or fail to provide practical application-specific details, this review summarizes IPS developments directed specifically towards mobile robotics. It examines and compares a breadth of approaches that vary across non-radio frequency, radio frequency, and hybrid sensor fusion systems, through the lens of performance metrics that include accuracy, delay, scalability, and cost. Distinctively, this work explores emerging innovations, including synthetic aperture radar (SAR), federated learning, and privacy-aware AI, which are reshaping the IPS landscape. The motivation stems from the' increasing complexity and dynamic nature of indoor environments, where high-precision, real-time localization is essential for safety and efficiency. This literature review provides a new conceptual, cross-border pathway for research and implementation of IPS in mobile robotics, addressing both technical and application-related challenges in sectors related to healthcare, industry, and smart cities. The findings from the literature review allow early career researchers, industry knowledge workers, and stakeholders to provide secure societal, human, and economic integration of IPS with AI and IoT in safe expansions and scale-ups.

1. Introduction

In an increasingly automated and intelligent world, mobile robots are transforming industries, enhancing services, and redefining human-machine interactions, from optimizing logistics in warehouses to providing critical assistance in healthcare scenarios. These adaptable machines drive far-from-basic advancements across all fields [1, 2]. The indoor positioning system (IPS) supports all of this. Unlike outdoor robots that rely on global navigation satellite systems (GNSS), mobile robots operating indoors must deal with serious challenges – they must navigate complex, dynamic, and often-cluttered environments with precise and reliable performance, multiplied by the need for scalable and effective IPS solutions. Therefore, the steady evolution of these systems creates great promise for intelligent automation inside industries wherein traditional navigation systems would fail [3, 4].

Indoor positioning systems represent a group of technologies that estimate the location and orientation of a mobile robot with respect to its environment. Indoor positioning systems support increasing robots' autonomy and providing various applications in manufacturing, retail, public safety, and smart infrastructure. However, the series involved in achieving reliable indoor positioning is filled with challenges [5, 6]. Obstruction by signals, multi-path effects, variations in environmental conditions, and differences in deployment scenarios all create an extremely challenging scope for researchers and engineers alike. Such constraints drove IPS from simple systems based on visual markers or radio frequency tags toward high-level solutions that involve fusion of multiple sensors, machine-learning algorithms, and advanced computational models [7, 8]. One of IPS's most attractive benefits is its interdisciplinary nature that bridges robotics, computer vision, signal processing, and artificial intelligence (AI). For example, the Light Detection and Ranging (LiDAR) and camera-based simultaneous localization and mapping (SLAM) systems utilize the latest vision algorithms to create detailed maps of their environment so that robots can traverse it very precisely [9, 10]. Also, some radio-frequency technologies, such as Ultra-Wideband (UWB) Radio-Frequency Identification (RFID), have led to the rise of low-cost, scalable solutions becoming more common in logistics and retail environments. However, within these approaches lie the respective advantages and disadvantages, leading to a constant motivation for innovation, allowing for the conclusion of unsolved problems [11].

The demand for indoor localization is more challenging than outdoor localization due to the' generally rather dynamic and unpredictable nature of indoor environments. While GPS signals can operate comparatively smoothly in open spaces, their effectiveness in indoor spaces is severely restricted due to walls, ceilings, and other structural hindrances [12–14]. Somewhat increased density in objects and human activity in indoor environments requires Indoor Positioning Systems (IPS) to account for constant changes in the surrounding environment. Hence, real-time accuracy becomes an essential requirement for IPS, because any delay or errors in localization may cascade problems in navigation and task execution. Examples in healthcare justify the demand for high precision. In a hospital, mobile robots delivering medications or sterilized equipment must navigate winding ways and avoid colliding with patients and staff members. In industrial settings, robots maneuver between racks in aisles and need centimeter-level accuracy for proper work and safety. Thus, these examples show that IPS serves not just as facilitators of robotic mobility but are interdependent components toward ensuring the success of many applications [15–17].

The evolution of IPS merges technological advances from various domains. Vision-based systems, for example, have seen a remarkable transformation by incorporating deep learning models capable of semantic segmentation and scene recognition. Neural networks allow the robot to build a map of the environment and identify and categorize objects inside the environment, thus providing the robot with some degree of contextual awareness [18, 19]. This capability is highly valuable when interacting with specific objects, such as in industrial tasks like picking and placing. On the other hand, radio-based systems have tapped into innovations in signal processing and hardware miniaturization. Cost-effective UWB and Bluetooth systems have the potential to be developed in high quantities and deployed in many environments, such as retail shops and airports. Although scalability and inexpensive installation make them attractive, many are left wanting due to high electromagnetic activity, causing interference in their operations and degrading signals [20]. To solve these limitations, researchers are working on hybrid systems incorporating radio-based localization that work together with vision or inertial measurement units (IMUs) to boost accuracy and reliability. New technologies, such as synthetic aperture radar (SAR) and LiDAR, are expanding the scope of what IPS might accomplish. While SAR is traditionally used in aerospace and defense, it has undertaken new applications in mobile robotics to support high-resolution mapping in low-visibility environments [21]. LiDAR continues to underpin indoor navigation, providing complex 3D maps that robots can navigate precisely. However, the prohibitive cost and computational complexity of LiDAR sensors are a key barrier stopping wide adoption of these systems, particularly in cost-saving applications [22–25].

Although new technologies have pushed the limits of the performance of IPS, this development is not without its challenges. One of the main issues is balancing accuracy, scalability, and cost [26, 27]. High-precision systems like LiDAR and SAR frequently entail huge expenses and heavy demands for processing power, rendering them impractical for many applications. On the other hand, less expensive solutions, often based on Wi-Fi or Bluetooth, have poor accuracy and reliability, especially in environments with heavy interference or mobile obstacles [28]. Other challenges include the integration of multiple sensing modalities. Hybrid systems, which blend visual, inertial, and radio-based sensors, hold great promises to mitigate the limitations of each individual technology. Nevertheless, seamless integration relies on sophisticated sensor fusion algorithms to process and reconcile data from impossibly disparate sources in real time [29]. This is a nontrivial task, particularly because each sensor type has its own noise characteristics, biases, and latency issues.

The role of intelligent machines in overcoming these challenges cannot be overstated. Machine learning algorithms, primarily built on foundation drivers such as reinforcement and federated learning, introduce new capabilities in the IPS field. Such systems can leverage past data to adjust to changing environments, thus improving their robustness and accuracy further down the line. In the case of the federated learning models, multiple collaborator machines can work together on improving the localization ability while assuring data privacy, a high consideration in any IBM application, such as healthcare and retail [30–32]. The evolution of IPS will show more possible opportunities for changes in the economy in industries and redefine their relations with humans via robots [33]. The synergy between IPS and the greater IoT ecosystem could lead to possibilities we might not have imagined before, where robots, innovative technologies, and even humans collaborate on this [34–36]. In the case of smart cities, IPS would enable delivery robots to work cooperatively to find optimal routes based on current traffic and environmental data; similar ideals extend to healthcare, wherein IPS, along with wearable devices, could establish patient monitoring and support functions at an advanced level [37, 38]. With that aside, however, there is still much work to do. IP implementation must be established safely and ethically, protecting data privacy and security. Moreover, to push the widest possible entry into the industry and ease coexistence with others, measures must be taken to develop standards and benchmarks to evaluate IPS performance.

In contrast to existing literature, which predominantly offers technology-specific or siloed perspectives, this review provides a comprehensive and integrative synthesis of Indoor Positioning Systems (IPS) explicitly tailored to the needs of mobile robotics. Prior works, such as Rekkas et al. [39] focus narrowly on AI methodologies in Visible Light Positioning (VLP) systems, overlooking other modalities like SLAM or SAR, while Liu et al. [40] discuss indoor VLC systems in a generic context without technical depth on mobile robot adaptability or cross-modal fusion. Similarly, Panigrahi et al. [41] offer a structured review of localization strategies using SLAM and probabilistic methods but exclude recent advancements in AI, edge computing, or federated architectures. Tan et al. [28] address RF-based IPS techniques but do not cover non-RF solutions and lack a robotic-centric outlook. Huang et al. and Yin et al. explore multiple IPS methods for mobile robots. Yet, their discussions are limited to classic methods and do not evaluate emerging technologies like synthetic aperture radar (SAR), real-time sensor fusion, or the implications of privacy-aware AI systems [21, 42]. Other articles, including those by Ullah et al. and Solanes & Gracia (2025), emphasize broad themes such as trajectory control and localization theory but provide neither empirical performance comparisons nor application-specific breakdowns in healthcare or public infrastructure [12, 43]. This review fills these critical gaps by (i) unifying non-RF, RF, hybrid, and AI-powered IPS technologies under one framework; (ii) offering comparative performance metrics such as accuracy, latency, cost, and scalability; (iii) highlighting underexplored technologies like SAR, federated learning, and cross-modal sensor fusion; and (iv) mapping their real-world applicability in healthcare, industrial automation, education, and smart cities. By addressing both the technical and application layers, this work delivers a uniquely balanced, forward-thinking roadmap for innovation in mobile robot localization, offering relevance to both early-career researchers and industry professionals. This review is structured into thematic sections to guide readers through this multifaceted topic. This review is divided into sections that build on each other logically and are intended to systematically introduce the IPS technologies applicable to mobile robotics. Section 2 defines and discusses standardized performance metrics and benchmarking tools applicable to evaluating IPS, allowing for an objective comparison base. Section 3 comprehensively categorizes IPS technologies, starting with non-RF categories, such as IMUs, LiDAR, infrared, VLC, and SLAM. Section 4 discusses the RF-based methods

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of IPS, namely Wi-Fi, Bluetooth, RFID, and UWB, with accompanying hybrid system discussions. Finally, Section 5 identifies major ongoing issues and research gaps such as trade-offs for accuracy vs cost, difficulty with sensor fusion, and privacy.

2. Performance metrics and benchmarking in IPS

Standardized performance metrics are critical for assessing and comparing different IPS technologies. Terms such as "accuracy," "reliability," and "efficiency" are frequently referenced in IPS literature; however, they are often left undefined or are used inconsistently. This section aims to clarify some essential metrics used to evaluate IPS performance and describe how they are measured and interpreted in practice. (1) Accuracy is one of the more important metrics to consider when assessing IPS performance. Accuracy refers to how closely an estimated position corresponds to the ground truth (actual position). It is generally expressed in meters or centimeters and computed as the Euclidean distance between estimated and true coordinates. In most real-world applications, anything less than one meter of accuracy is considered sufficient (like with industrial warehouses); however, sub-10-centimeter accuracy is often recommended for practical applications in medical robots, UAVs, or other precision healthcare tasks. Precision is another metric that is closely associated with accuracy. Unlike accuracy, (2) precision concerns the repeatability of position estimates under the same or similar environmental conditions. Precision is generally measured by the variance or standard deviation of position estimates. Significant precision in IPS performance means that the estimations are stable, and in static or semi-dynamic environments, little drift can result in compounding errors over time [44, 45]. (3) Reliability, however, is the capability of the system to provide accurate localization consistently for a duration of time and over a range of conditions. The reliability of the system is usually displayed as a percentage of the time the system was localized within a set error window (e.g., <50 cm error) during operation; for example, if the system was localized within a set window 80% of the time, the reliability value is typically considered 80%. (4) Latency (response time) refers to the delay from when a positioning request is made until a valid position estimate is obtained. Latency is expressed in milliseconds, and with robotic navigation systems, it is usually expected to be <100 msto operate safely and efficiently in a real-time scenario. Infrared and VLC systems provide a lower latency than interfacing with a cloud-based AI-enhanced IPS. (5) Scalability is an important consideration, especially in environments where multi-user support or a much larger coverage area is necessary. Scalability denotes the IPS's ability to maintain performance as the number of tracked objects or the covered area increases. Scalability can be quantified using objective parameters by monitoring any performance degradation with increasing load or listed subjectively by analyzing the system architecture [46]. (6) Another salient performance metric is coverage area; the maximum extent of indoor space in which the IPS can yield reliable indoor operation must be defined in pixels to square meters. Coverage area varies wildly between potential IPS technologies: For example, there are IPS solutions available or technically feasible in very confined spaces like hospital rooms, while there are some technologies that can service a bigger coverage area, such as warehouses, freight terminals, and shopping malls. Many IPS have distinct performance metrics that researchers and practitioners do not consider when evaluating routine applications. However, researchers and practitioners can consistently and comparably assess the performance of indoor positioning systems, using a selection of benchmarks and datasets. Benchmarks include these frameworks: EvAAL (evaluation of AAL systems) has existing benchmark test environments, the UJIIndoorLoc, a dataset used in Wi-Fi fingerprinting, and room-related IPS datasets used for spatial awareness, based on brochure, room Alive, or orbit data, are popular datasets for evaluating camera-based systems. In robotics IPS, SLAM Bench (benchmarking using simultaneous Localization and Mapping) or ROS (robotics operating system, or more specifically, map-based platforms) should become a standard benchmark for evaluation to consider and evaluate real-time performance, accuracy, energy efficiency, and consumption consideration under the assumptions of scale-configurable environments [47]. By defining and framing performance metrics of accuracy, precision, reliability, latency, scalability, energy consumption, and coverage, this section

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Table I. *Summary of standard performance metrics for IPS [44–47].*

Metric	Definition	Unit of measure	Importance in IPS	Typical thresholds
Accuracy	Closeness of estimated location to actual ground truth	meters or centimeters	Critical for precise navigation in healthcare, robotics	<1 m (general); <10 cm (surgical robots)
Precision	Repeatability of position estimates under similar conditions	Variance, Std. Deviation	Ensure consistency; reduces cumulative error	Low variance preferred
Reliability	The system's ability to maintain accuracy over time and conditions	% Time within error window	Key for performance consistency in dynamic settings	≥80% within the specified range
Latency	Time delay from request to position estimation	Milliseconds (ms)	Crucial for real-time robotic response	<100 ms ideal
Scalability	Ability to handle the increased number of devices or areas without performance loss	Qualitative / Stress tests	Necessary for smart buildings, multi-robot systems	Performance degradation % under load
Coverage	Physical space over which IPS is effective	Square meters/pixels	Helps determine feasibility for larger installations	Context-specific
Energy efficiency	Power required to operate the IPS modules	Joules, Watts	Important for mobile devices and wearables	Lower is better

better conveys the technical complexity of evaluating IPS. Researchers and practitioners can weigh and select positioning systems when and where they are relevant to environments and application-specific situations. A summary of these performance metrics is provided in Table I.

3. Classification of indoor positioning systems

This section describes how IPS classified them into non-radio-frequency, radio frequency, and hybrid systems. This classification highlights the technological diversity in IPS and various capabilities and limitations. The section compares LiDAR to Visual SLAM and Wi-Fi to UWB and compares their performances across different environments. Furthermore, it elaborates on hybrid systems that combine various technologies into one, gaining accuracy and efficiency by showing how and where they work in real applications. This extensive classification can justify the potential. The exposition provides a foundation for understanding India's complex situation and the prospects of IPS technologies.

3.1. Non-radio frequency methods

This section focuses on non-radio-frequency methods, technologies that do not rely on radio signals for indoor positioning. Such methods occupy a conspicuous role in scenarios whereby the radio frequency-based systems experience difficulties – either due to interference or regulation restrictions.

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3.1.1. Inertial measurement units (IMU)

Blind and moving around a room is how the IMU works for a robot. IMUs are electronic devices that fit within robots and can sense and even interpret their motion without external help, including signals from radio waves or light. An IMU comprises two components: an accelerometer that measures the acceleration, such as how fast the robot goes forward or backward, and a gyroscope that mostly senses if the robot tilts or turns. Some of these systems have a magnetometer as one of their components, which acts as a compass to determine the directional orientation [48, 49]. Together, all this provides information crucial for robots to navigate indoor spaces. IMUs are simple to understand. An accelerometer senses if a robot is moving or not in the forward, backward, upward, or downward directions, quite like the feeling a person gets from the acceleration and deceleration of a vehicle [50, 51].

By combining sophisticated perception capabilities, IMUs are changing the playing field for indoor navigation by tackling the complex technical challenges of localization. The ENDORSE project by Ramdani et al. is a prime example (Figure 1A). The ENDORSE project harnesses the accuracy of SLAM and fuses wireless sensors to create infrastructure-less robotic navigation in hospital scenarios. The ENDORSE project uses a dynamic modular architecture built on HLAA-compliant cloud infrastructure to carry out modular tasks such as UV sanitization or diagnostics, which can be dynamic and carry out hybrid tasks [52]. Building on this, Cheng et al. (Figure 1B) proposed a system combining binocular vision with IMU data, where an asynchronous Kalman Filter fuses visual corner detection with inertial data to reduce drift, ensuring high-precision navigation even in low-texture environments [53]. This evolution continues with Yan et al. (Figure 1C), who integrated LiDAR and IMU data using Kalman filtering to enhance positioning accuracy in dynamic or occluded spaces [54]. Shifting focus to rugged construction sites, Ibrahim et al. (Figure 1D) introduced a jerk-based IMU localization approach that uses triple jerk integration and barometric sensors for precise, infrastructure-free tracking [55]. Cramer et al. (Figure 1E) have benchmarked low-cost IMUs for AGVs for scalable industrial applications to demonstrate performance like premium IMUs [56]. The use of these low-cost IMUs is now being extended to more unconventional applications, as Cole et al. (Figure 1F) have shown the use of IMUs for biobotic insects in disaster robotics, where accurate path reconstruction was performed via machine learning. Both cases illustrate the evolution and versatility of IMUs in contemporary navigation systems [57].

From healthcare to industrial automation and disaster response, these case studies underscore the transformative potential of IMUs when integrated with complementary technologies. Together, they vividly picture how precise indoor navigation systems reshape diverse industries. To consolidate the insights gained from the diverse applications of IMUs across various domains, Table II provides a comprehensive comparative analysis of the discussed case studies. This table captures each study's unique contributions, strengths, limitations, and overarching trends, offering a clear perspective on the evolution and versatility of IMU-based systems. The table complements the detailed narratives by summarizing the technical nuances and practical applications, ensuring a holistic understanding of these innovative approaches.

3.1.2. Visible light communication (VLC)

VLC holds transformative potential for indoor remote mobile robotics systems, providing reliable, high-speed communication, and precise positioning, which are essential for autonomous navigation and operations. VLC uses LED lights as transmitters, modulating their intensity to encode data, which is then received by robots equipped with photodetectors or image sensors. This dual functionality of LEDs for illumination and communication makes VLC an energy-efficient and cost-effective solution for enhancing the capabilities of indoor robotics [64]. VLC is becoming a very powerful technology for high-precision indoor positioning, especially in areas with limitations of traditional RF systems. Li et al. (Figure 2A) designed a VLC system using smart LED lamps with Bluetooth controls and LED-ID algorithms with a centimeter-level (sub-2.14 cm) accuracy. They supported robot speeds of up to 20 km/h. This makes it perfect for fast-paced, dynamic indoor environments like office spaces [65]. To

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Table II. *Comparative analysis of IMU-based localization and application case studies.*

Ref. Nos.	Focus	Strengths	Limitations	Key techniques	Applications	Overarching trends
[58]	Using deep neural networks for reducing drift in low-cost IMUs for indoor odometry	Learns motion characteristics and corrects systematic errors; adaptable to dynamic motions	Requires extensive training data for neural networks; computationally intensive	Deep neural networks, sequential learning, trajectory reconstruction	Indoor pedestrian navigation, retail spaces, and dynamic environments	Deep learning techniques are gaining prominence for trajectory estimation and drift correction.
[59]	Pedestrian dead reckoning with chest-mounted IMU and map-matching for 3D navigation	Accurately computes step length and direction; integrates with a map-matching algorithm	Chest-mounted position may not suit all scenarios; dependent on initial calibration	Step-length estimation, chest-mounted IMU, particle filtering	Multifloor navigation, emergency evacuations, and large buildings	Chest-mounted IMUs introduce new possibilities for upper-body motion tracking.
[60]	Simultaneous indoor localization and mapping using IMU and BLE beacon fusion	Reduces configuration effort; adapts to dynamic environments; highly accurate localization	It depends on the deployment of BLE beacons; less suitable for large, open spaces	Kalman filters, BLE beacon data fusion with PDR	Smart homes, healthcare monitoring, and indoor navigation	Hybrid solutions combining IMU and environmental sensors are emerging as robust systems.
[61]	Estimating human joint angles using IMUs with UKF, validated with a robot arm	Integrates anatomical constraints and zero-velocity updates to reduce sensor drift	Performance degrades with prolonged use due to sensor drift	Unscented Kalman Filter, Kinematic modeling, sensor drift modeling	Clinical motion analysis, rehabilitation, and wearable technology	Advanced filtering techniques and anatomical constraints are improving IMU precision.
[62]	Combining IMU data with IP camera visual measurements for improved indoor positioning	Reduces positioning errors in dense multipath scenarios; leverages visual detection and IMU fusion	Requires fine-tuning of Faster R-CNN; dependent on stable camera networks	Extended Kalman Filter, Faster R-CNN, Monocular Vision Relatively Measuring	Indoor navigation, retail monitoring, and smart cities	Incorporating visual data into IMU systems is an effective way to enhance indoor localization.
[63]	Assessing IMU accuracy with industrial robots under various dynamic conditions	Provides robust validation protocol; accurate in electromagnetic noise-prone environments	Restricted to controlled settings; less applicable for free-form environments	Kalman filter, complementary filter, gradient descent filter	Validation of IMU-based applications in controlled lab environments	Comprehensive validation methods are critical for establishing IMU accuracy in dynamic contexts.

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Figure 1. *(A) The development of infrastructure-less navigation for healthcare logistics, taken from ref. [52], with the permission of IEEE. (B) Binocular vision and IMU-based system for GPS-denied environments, taken from ref. [53], copyright sage publication. (C) indoor mobile robots for navigation positioning, replicated from ref. [54], copyright Sage Publication. (D) IMU system-based indoor robots for infrastructure-independent localization, taken from ref. [55], Copyright Elsevier. (E) Low- and medium-cost IMUs for automated guided vehicles for cost-effective navigation in industrial applications, taken from ref. [56], Copyright Elsevier. (F) IMU-based system for trajectories in GPS-denied environments, taken from ref. [57], Copyright MDPI.*

elaborate further, Guan et al. (Picture 2B) connected VLC to the Robot Operating System (ROS) for the TurtleBot3 robots using video tracking and double-lamp positioning combined with an enhanced version of Camshift–Kalman. The updates from the sensor resolved to an accuracy of 1 cm, with every update being processed every 0.4 s. This demonstrates how feasible the integration of VLC with ROS is going forward for robots at a higher level of sophistication [66]. The next area of optimization is

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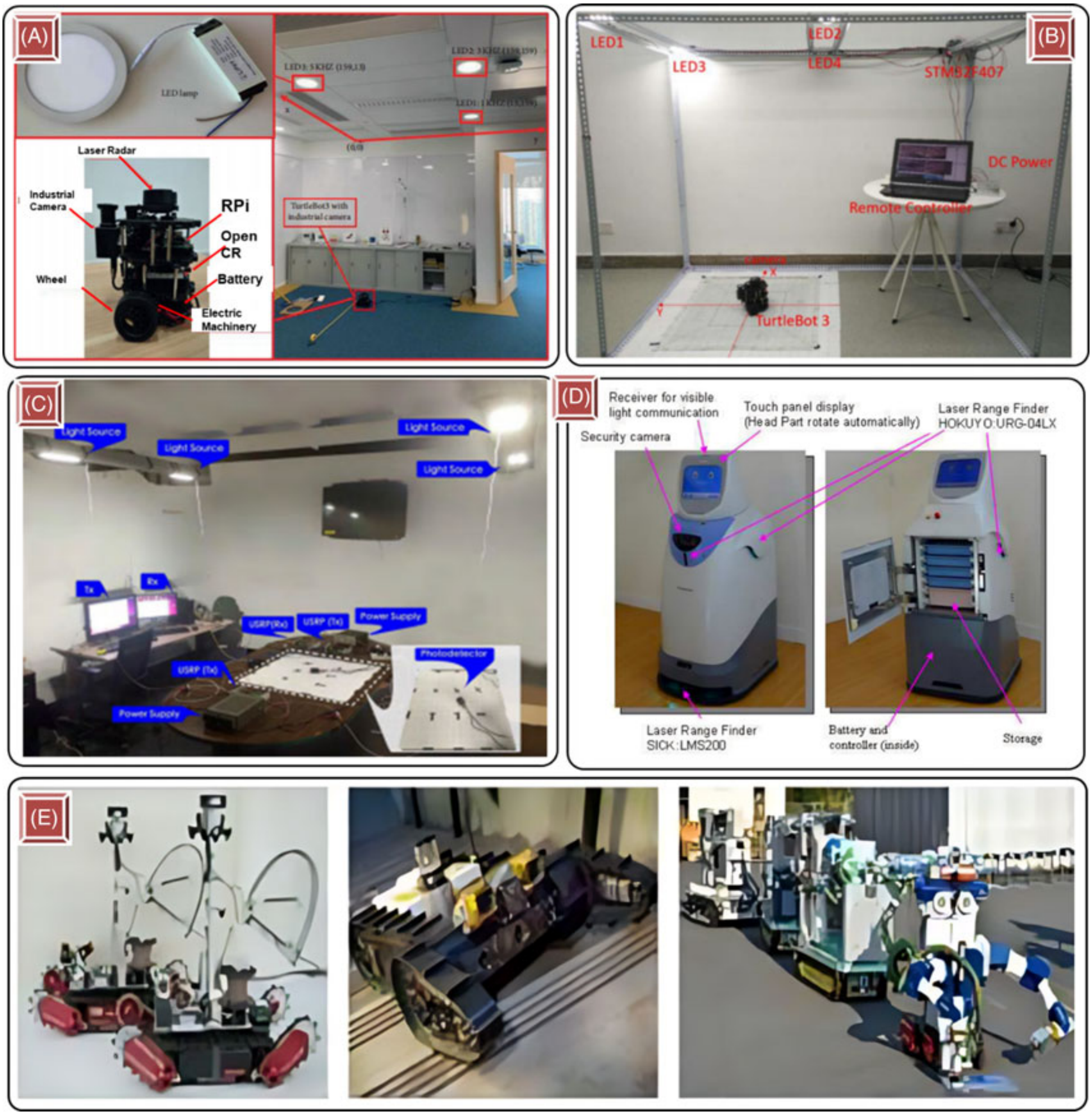

Figure 2. *(A) VLP system for mobile robots for dynamic indoor environments, taken from ref. [65], Copyright Hindawi. (B) VLC-based localization system for indoor navigation, taken from ref. [66], copyright arXiv. (C) Two-layer fusion network spanning industrial automation and smart buildings, taken from ref. [68], copyright IEEE. (D) VLC-based autonomous delivery robot to improve hospital safety and navigation, taken from ref. [69], copyright IEEE. (E) VLC-based positioning system for mobile robots in nuclear power plants, taken from ref. [70], copyright axXiv.*

machine learning. Tran and Ha [67] (Figure 2C) achieved a 78.26% reduction in processing time and a 52.55% increase in accuracy using noise reduction and dual-function machine learning algorithms. In another study with at least partially different machine learning methods, Guo et al. introduced a Two-Layer Fusion Network to further improve localization through the integration of various fingerprints and classifiers, even when the variation of LED was burdened by variation in power [68]. Then, also applied in practice, in the health sector, Murai et al. (Figure 2D) outfitted the HOSPI robot with LED mapping using VLC to support safe navigation of hospitals and avoid hazards on the pathways, for example, stairs [69]. In the case of nuclear power plants, Xie et al. (Figure 2E) offer a VLC system enabling navigation

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using radiation-shielded LEDs and a dispersion-calibrated algorithm, which enabled accuracy within a few centimeters in high-radiation environments [70]. The illustrative case studies described above mention the various applications and advantages of VLC technology being utilized in indoor robotic systems, ranging from precise navigation to robust communications in challenging environments. These conclusions are supplemented by a tabular comparative analysis summarizing a consolidated account of these findings and what technological contributions can be derived from them.

Moving off from the setup of experimentation and the design achievement from the case studies, entrapping a whole platform upon which VLC throws in all its bridges inside different applied fields, employing Table III.

3.2. Non-radio frequency methods

Infrared systems have found extensive application in indoor robotics for communication, navigation, and detection of obstacles. They are based on invisible infrared light waves, generated from IR LEDs or similar equipment, and received by photodiodes or infrared cameras. The IR emitter, therefore, sends some light pulses, modulated to carry information regarding the distance of objects, their positions, or command instructions. The receiver detects the pulses and translates them into electrical signals, which are then processed to decode the transmitted data [28]. In navigation, IR systems often rely on triangulation to determine the robot's position. By measuring the time it takes for infrared signals from multiple emitters to reach the robot, its location can be calculated with high precision. For obstacle detection, IR sensors emit light and measure the time it takes for the reflected signal to return or the strength of the reflection, helping the robot estimate the distance to nearby objects and avoid collisions. Additionally, infrared communication allows robots to exchange data in environments where radio frequencies might cause interference. The working principle of IR systems highlights their utility in indoor robotics for precise navigation, obstacle detection, and secure communication. These fundamental capabilities form the basis for various innovative applications across diverse environments, from small-scale setups to large, dynamic spaces [75, 76].

For instance, Raharijaona et al. developed a minimalistic indoor localization system using flickering infrared LEDs and bio-inspired sensors. By utilizing amplitude-modulated infrared signals, the system achieves azimuth and elevation angle estimation with an accuracy of 2 cm at a 2 m range and a sampling frequency of 100 Hz. The compact design, 10 cm^3 in size, weighing 6 g, and consuming just 0.4 W supports low-cost, energy-efficient operation, as shown in Figure 3 (A). The sensor demonstrated robustness to diverse lighting conditions, including darkness and flickering light, making it suitable for GPS-denied environments like indoor robotic applications. Its Arduino-compatible demodulator further emphasizes its accessibility and practical use in trajectory tracking [77]. Building on the theme of dynamic indoor positioning, Awad et al. introduced a collaborative approach to localize access points (APs) using a swarm of autonomous robots. By collecting non-uniformly distributed RSSI samples, the system efficiently estimates AP locations without prior knowledge of the environment. Tests confirmed its precision and reduced reliance on manual labor, demonstrating scalability and robustness for complex indoor settings. This solution provides a cost-effective way to address issues like rogue APs in wireless networks, as shown in Figure 3 (B) [78]. Extending to industrial environments, Cretu-Sîrcu et al. compared ultrasonic (GoT) and UWB technologies for indoor localization (as shown in Figure 3 (C)). Static tests showed localization errors of 0.3–0.6 m, while dynamic tests with a robot moving at 0.5 m/s revealed GoT's superior accuracy of 0.1–0.2 m, compared to Pozyx's 0.3–0.4 m. Although UWB excelled in mixed LoS/NLoS conditions, GoT was particularly effective for mobile robotics, meeting industrial accuracy requirements [79]. Finally, Qi and Liu presented a high-accuracy ultrasonic indoor positioning system (UIPS) based on wireless sensor networks. Using time-of-flight measurements and synchronized ultrasonic beacons, the system achieved a maximum localization error of 10.2 mm and a precision of 0.61 mm under line-of-sight conditions (as shown in Figure 3 (D)). Its cost-effective, robust design ensures suitability for dynamic, cluttered spaces, making it ideal for industrial and healthcare applications requiring high precision [80]. These studies illustrate the versatility and advancements in

Table III. *Comprehensive analysis of VLC-based indoor robotics systems.*

Ref. Nos.	Focus	Strengths	Limitations	Key techniques	Applications	Overarching trends
[67]	Optimizing positioning accuracy and speed under multipath conditions using ML.	52.55% accuracy improvement; reduces computational time by 78.26%.	Prone to noise and multipath interference in some setups.	Noise reduction, area division, ML regression, and classification.	Retail, healthcare, and dynamic indoor positioning.	ML integration addresses noise and enhances efficiency.
[71]	Combining VLP with IMU data for robust positioning under LED outages.	Maintains accurate positioning even under LED outages; 2.1 cm average error.	Dependent on proper IMU calibration for accuracy.	Extended Kalman Filter (EKF), IMU-VLP fusion.	Indoor localization for robotics in dynamic or obstructed spaces.	Sensor fusion enhances reliability under challenging conditions.
[72]	Integrating VLP and SLAM with LiDAR for precise navigation and mapping.	Provides 2.5 cm accuracy and robust mapping in dynamic environments.	Requires dense LED deployment for initialization.	LiDAR-SLAM, multi-sensor fusion, EKF-based localization.	Warehouse automation, long-term autonomous navigation.	Combining VLP with SLAM broadens functionality to mapping and navigation.
[73]	Combining pose assistance and VLP for enhanced indoor positioning in complex spaces.	It achieves 5 cm plane and 6 cm height accuracy, and it is cost-effective and scalable.	Performance depends on light source layout; limited scalability to dynamic environments.	VLP imaging methods, LED-ID recognition, and IMU-assisted pose estimation.	Urban lifeline navigation, underground and indoor construction projects.	Integration of imaging and pose assistance enhances VLP accuracy for enclosed environments.
[74]	Using smartphone cameras for VLC-based indoor positioning through the rolling shutter effect.	Utilizes existing smartphones; robust against RF interference; provides high localization accuracy.	Susceptible to noise from external light sources; limited to compatible Android devices.	Rolling shutter effect, OOK modulation, Manchester encoding for robust data decoding.	Smart homes, retail spaces, museums, and healthcare facilities.	Smartphone-based solutions make VLC practical and accessible for indoor navigation.

indoor localization technologies across varied applications and environments. These advancements in indoor localization demonstrate the growing diversity of techniques and technologies tailored to meet specific application needs, from robotics and industrial automation to healthcare and public spaces.

A detailed comparative analysis of selected IR-based indoor localization systems is provided in Table IV below. This comparison highlights the focus, strengths, limitations, key techniques, and applications of each system, offering insights into overarching trends shaping the development of these innovative solutions.

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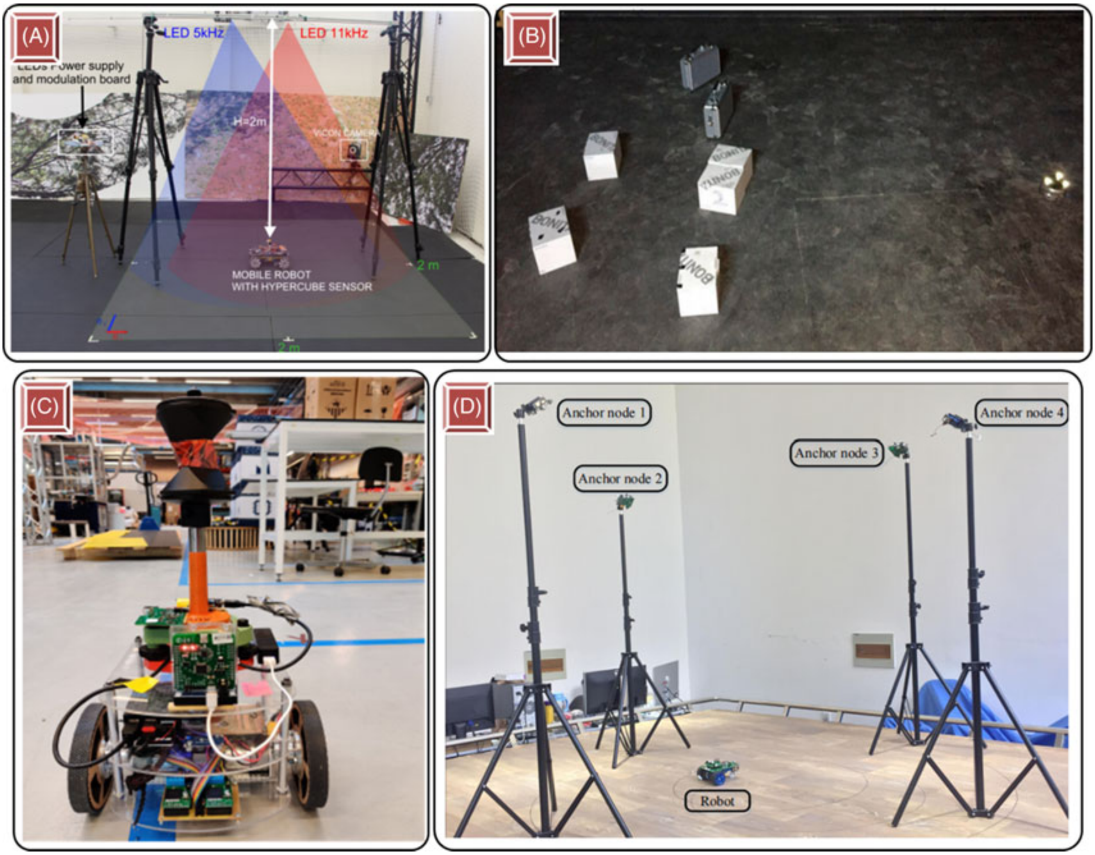

Figure 3. *(A) Indoor localization system using flickering infrared LEDs and bio-inspired sensors suitable for GPS-denied environments like indoor robotic applications, taken from ref. [77], Copyright MDPI. (B) Swarm of autonomous robots for complex indoor settings, taken from ref. [78], Copyright MDPI. (C) Mobile robotics based on ultrasonic and UWB technologies for indoor localization, taken from ref. [79], copyright MDIP. (D) High-accuracy ultrasonic indoor positioning system (UIPS) based on wireless sensor networks, taken from ref. [80], copyright MDIP.*

3.2.1. Light detection and ranging (LiDAR)

LiDAR technology measures distances and creates detailed maps for indoor environments using laser light. Technology consists of laser pulses that reflect off objects or surfaces, measuring the time the laser light travels back after reflecting. The measured time-of-flight data are then used to compute the distance to the object, which helps the robot get a better picture of what is around it. LiDAR systems do either a sweep or a rotation across a broad area to collect millions of data points, which are integrated together to create a 2D or 3D map of the environment. Within indoor robotics, it is paramount for navigation, obstacle detection, and mapping [89]. Robots with LiDAR could precisely identify walls, furniture, and other objects, allowing them to move safely and plan efficient paths in dynamic environments. For example, a delivery robot in a hospital could use LiDAR to navigate through crowded hallways and avoid obstacles, such as other people or carts. Furthermore, LiDAR supports SLAM algorithms that enable robots to build and update maps dynamically while keeping track of where they are within those maps [90].

LiDAR technology has become foundational in indoor robotics due to its precision, low-light operability, and capability to navigate complex layouts. Despite limitations such as poor performance on reflective or transparent surfaces and high costs, LiDAR remains crucial for accurate mapping and autonomous indoor navigation. A key example is the real-time LiDAR-based SLAM system developed by Zhang et al. (Figure 4A), which utilizes scan-to-map matching and adaptive loop closure to

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Table IV. Comparative study of indoor localization systems based on IR.

Ref. Nos.	Focus	Strengths	Limitations	Key techniques	Applications	Overarching trends
[81]	Fusion of cameras and infrared sensors for indoor positioning.	Achieves sub-centimeter accuracy in most tested positions; cost-effective and scalable.	Limited to specific environmental setups; sensitive to lighting conditions.	Sensor fusion, maximum likelihood estimation, and variance propagation.	Industrial spaces and smart environments.	Fusion-based systems enhance precision and robustness in complex indoor spaces.
[82]	Three-photodetector optical sensor for mobile robot localization.	10 cm accuracy at 3 m; robust to environmental variations; low-cost design.	Limited to small-scale setups; sensitive to beacon placement.	Extended Kalman filter, complementary filter, and radiometric modeling.	Mobile robotics and critical industrial areas.	Optical sensor-based solutions emphasize cost-efficiency and robustness for mobile robots.
[83]	Wiimote-based 2D localization for mobile robots.	Provides accurate 2D tracking using off-the-shelf hardware; integrates feedback control.	Limited to 2D localization; performance decreases in complex environments.	Coordinate transformation, Wiimote tracking, trajectory feedback control.	Indoor navigation and mobile robotics.	Leveraging commercial gaming hardware for localization in intelligent systems.
[84]	Low-cost light system for indoor robot self-localization.	Cost-effective, innovative ID encoding; suitable for large-scale setups.	Restricted by ID limitations and low computational resources.	IR LEDs, Monte-Carlo localization, novel ID arrangement.	Indoor navigation in public spaces like malls and museums.	Affordable localization systems targeting large-scale indoor environments.
[85]	Infrared Angle of Arrival (AoA) sensor for indoor localization.	Centimeter-level accuracy in static scenarios, low cost, and real-time navigation support.	Limited accuracy in dynamic contexts; sensitive to signal propagation issues.	Infrared AoA, wireless sensor networks, pragmatic design.	Supermarkets and retail spaces.	Exploiting IR-based AoA for affordable and accurate navigation in commercial spaces.
[86]	Multi-sensor fusion for human-following robot navigation.	Handles dynamically changing environments, reliable obstacle avoidance, and human tracking.	Computationally intensive; requires multiple sensors.	Depth camera, active IR marker, and proximity sensors fusion.	Companion robots for elderly or disabled users.	Multi-sensor fusion improves robustness and accuracy in human-following tasks.
[87]	3D position and orientation measurement for mobile robots using photoelectric scanning.	3.8 mm position accuracy and 0.104° orientation accuracy in a large-scale environment.	Requires precise landmark calibration; sensitive to environmental conditions.	Photoelectric scanning, rotary laser, multi-angle intersection.	Industrial automation and cargo handling.	Emphasis on 3D localization for high-precision applications in structured environments.
[88]	IR sensor array with k-means clustering for multi-robot localization.	Efficient multi-robot localization; reduced time for position estimation.	Accuracy depends on array density; it is sensitive to noise in signal propagation.	IR receiver array, k-means clustering, column scanning.	Multi-robot systems in industrial or public spaces.	Combining clustering algorithms with IR sensors for efficient multi-robot positioning.

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Figure 4. *(A) LiDAR-based SLAM system for autonomous robots, taken from ref. [91], copyright frontiers. (B) LiDAR-based robust for pose estimation in clean and perturbed environments [92], copyright MDPI. (C) self-adaptive Monte Carlo Localization algorithm tailored for smart automated guided vehicles position tracking, and kidnapping scenarios, taken from ref. [93], copyright elsevier. (D) LiDAR localization method leveraging multi-sensing data from IMU, odometry, and 3D LiDAR for complex indoor spaces, taken from ref. [94], copyright MDPI. (E) LiDAR and IMU integration for UAV indoor navigation, taken from ref. [95], copyright MDPI.*

enhance mapping consistency and reduce drift. It's integrated probabilistic data association ensures reliable localization even in dynamic environments [91]. Building on this, Wang et al. (Figure 4B) introduced a solution for improving LiDAR-based feature extraction using a weighted parallel ICP algorithm, which increases convergence speed and robustness, especially in structured indoor environments [92]. Building previous multi-sensor systems, Yilmaz and Temeltas (Figure 4C) created Self-Adaptive Monte Carlo Localization for smart AGVs incorporating 2D/3D LiDARs. Their energy model uses ellipses to be less sensitive to asymmetrical sensor placements in an industrial factory [93]. Liu et al. (Figure 4D) further enhanced LiDAR localization by fusing data from IMU, odometry, and 3D LiDAR through an Extended Kalman Filter and PL-ICP, delivering accurate localization without GNSS [94]. For UAVs,

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Kumar et al. (Figure 4E) integrated horizontally and vertically mounted LiDARs with IMUs to achieve 3D indoor navigation, which is useful in confined, dynamic environments like pipelines and disaster zones [95]. Lastly, Li et al. [24] created a hybrid indoor-outdoor navigation framework combining GNSS, INS, and LiDAR. This system seamlessly transitions between navigation environments with Hector SLAM and Kalman filtering. These studies collectively showcase LiDAR's adaptability and essential role in enabling robust, accurate, and context-sensitive indoor localization solutions across robotics and autonomous systems.

Such case studies illustrate the wide-ranging versatility of LiDAR technology in solving many localization and navigation problems. From single-sensor performance to multi-sensor integration, and from land-based robots to UAVs, LiDAR's versatility highlights its importance in furthering the technology for autonomous robotics. Each study is founded on the last, showing a progressive refinement of techniques to improve reliability, accuracy, and computational efficiency in indoor robotics applications. A complete comparison Table V integrates the strengths, weaknesses, and main trends of these studies as a follow-up to the findings of such studies.

While LiDAR, VLC, and IR systems have demonstrated significant utility in indoor positioning, their suitability varies based on deployment needs. LiDAR offers centimeter-level precision and excels in 3D mapping, but its high hardware cost and computational demands limit its scalability in low-cost applications. In contrast, VLC systems provide high localization accuracy and dual use for lighting and communication. Still, they are susceptible to ambient lighting and require line-of-sight, making them less robust in dynamic environments. IR systems are cost-effective and energy-efficient, with moderate accuracy, but suffer from limited range and poor performance in environments with signal occlusion or thermal interference. Table VI presents a side-by-side comparison of these technologies using core evaluation metrics relevant to indoor robotic navigation.

3.2.2. Visual simultaneous localization and mapping (SLAM)

Visual Simultaneous Localization and Mapping (SLAM) is a technology that enables robots to build a map of their surroundings while simultaneously determining their location within that map. It relies on visual data captured by cameras, such as monocular, stereo, or RGB-D cameras, to extract environmental information. The process involves detecting and tracking key features, such as edges, corners, or textures, in consecutive frames of the camera feed. The robot's camera captures images as it moves through the environment. Key features from these images are identified and matched across frames to estimate the robot's movement and orientation (pose). Using these pose estimations, the robot continuously updates its position and integrates new observations into the map. Advanced algorithms, like Bundle Adjustment and Loop Closure Detection, refine the map to reduce errors caused by drift or repeated patterns [41, 104].

Visual SLAM has become a cornerstone of autonomous indoor navigation, enabling robots to map and traverse unfamiliar environments. Its evolution through multi-sensor integration and advanced algorithms has led to diverse real-world applications. Roy et al (Figure 5A) [100], presented an exploration-based SLAM (e-SLAM) framework solely using LiDAR sensors, including mapping, localization, and path planning using a generalized Voronoi algorithm. Controlled gains reflect a proportional increase in fidelity, and as shown, navigate both robustly and effectively by all measures with minimal hardware. Beyond navigation, SLAM is being utilized, for example, by Yang et al. [105] (Figure 5B), as they let a SLAM-equipped robot monitor CO_2 levels indoors by mapping results spatially to the temporal sensing, the SLAM robot had a source detection accuracy of 1.83 m, effectively combining spatial mapping and temporal sensing. This approach is more economical and flexible than static sensors for environmental monitoring. For visually sparse and repetitive environments, Chen (Figure 5C) [106], proposed STCM-SLAM, fusing stereo vision and IMU data. By leveraging forward-backward optical flow and nonlinear optimization, this system outperformed ORB-SLAM2 and OKVIS in trajectory accuracy, proving effective in complex, low-texture settings. Singh et al. (Figure 5D) introduced a socially aware SLAM using adaptive neural networks concerning human-robot interaction. Tested at

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Table V. *LiDAR research overview.*

Ref. Nos.	Focus	Strengths	Limitations	Key techniques	Applications	Overarching trends
[24]	Seamless indoor and outdoor navigation using INS, GNSS, and LiDAR integration.	50% higher accuracy than Dead Reckoning; 80% success in navigation mode switching.	Complex switching algorithm for INS/LIDAR	INS/LIDAR integration, switching algorithms	Vehicular navigation in mixed environments	Expanding seamless navigation capabilities for vehicles
[90]	Semantic mapping for domestic robot navigation	Improved navigation through object semantics	Limited to static objects	2D LiDAR, RGB-D integration, SLAM	Home robotics for navigation and mapping	Bridging semantic understanding with navigation
[96]	Sparse feature environments for navigation	Effective trajectory tracking with low features	Dependency on learning-based classifiers	Improved Pure Pursuit algorithm	AGV navigation in sparse environments	Adapting to challenging low-feature spaces
[97]	SLAM and path planning for rescue robots	Balanced path optimality and obstacle avoidance; validated in rescue competition environments.	Lack of robustness in unknown environments	A∗, DWA algorithms, SLAM comparison	Indoor rescue missions, RoboCup competitions	Combining SLAM with real-time rescue applications
[98]	2D-LiDAR-based localization with correlative scan matching (CSM)	High precision and fast recovery from localization failures	Requires fine-tuned thresholds for pose estimation	CSM, low-pass filter, branch-and-bound method	Indoor mobile robot localization and navigation	Emphasis on robust and efficient pose estimation
[99]	Exploration-Based SLAM (e-SLAM) for mapping and localization	Real-time mapping and navigation without pre-built maps	Complex algorithms may limit scalability	LiDAR mesh generation, MSC alignment, LQE	Service robots in office and academic buildings	Combining exploration and SLAM for flexible deployment
[100]	Path planning and motion control under e-SLAM	Efficient path planning with obstacle avoidance	Relies solely on LiDAR, limiting data diversity	Dynamic-Window Approach (DWA), interpolation techniques	Indoor rescue missions, industrial robot navigation	Integrating SLAM with real-time path planning
[101]	Simplified structure-based loop closure detection	Efficient and robust global loop closure detection	Limited by low-resolution LiDAR	Simplified structure extraction, hierarchical matching	Indoor mapping with low-cost LiDAR sensors	Improving efficiency with simplified data processing
[102]	Indoor localization using LiDAR and dual AprilTags	Quick global localization with reduced computation	Dependent on proper AprilTag placement	AMCL, dual AprilTag positioning	Warehouse and factory automation	Enhancing accuracy by combining LiDAR and visual markers
[103]	Robust localization integrating CNN-based visual and laser localization	Handles robot kidnapping and provides accurate re-localization	Sensitive to environmental lighting conditions	CNN-based image retrieval, AMCL	Indoor mobile robot navigation in structured spaces	Fusion of visual and laser data for enhanced robustness
[89]	Autonomous navigation using 2D LiDAR and enhanced SLAM	Enhanced map accuracy and path planning efficiency	Suboptimal in highly dynamic environments	RBPF-SLAM, GBI-RRT path planning	Rescue operations, household automation	Advancing probabilistic SLAM techniques for dynamic tasks

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Table VI. *Comparative analysis of liDAR, VLC, and IR systems [28, 64–90].*

Feature	LiDAR	VLC	IR
Accuracy	Very high (cm-level)	High (sub-meter with dense LED grid)	Moderate (1–2 m typical)
Scalability	Moderate (cost-prohibitive for large setups)	Moderate (requires controlled lighting and dense LEDs)	Low to Moderate (limited by range and LOS)
Cost	High (sensor and compute-intensive)	Moderate (LED infrastructure needed)	Low (economical sensors)
Latency	Low (real-time with onboard processing)	Low to Moderate (dependent on pre-processing)	Low (fast response time)
Robustness	High (works in low light, cluttered environments)	Low (affected by ambient light and obstructions)	Low to Moderate (affected by heat, obstacles)
Environment Suitability	Warehouses, hospitals, UAVs	Offices, healthcare, and clean indoor spaces	Museums, retail, and small indoor areas
Advantages	High precision, Effective in cluttered/low-light environments, Strong support for SLAM and 3D mapping	Dual use for lighting & communication, High data rate, Good for EM-sensitive environments	Low cost, Fast response, Easy to deploy in confined indoor spaces
Disadvantages	Expensive hardware, High computational needs, Not ideal for highly reflective or transparent surfaces	Requires clear line-of-sight, affected by ambient lighting, and Limited in dynamic environments	Limited range and accuracy, Susceptible to thermal and light interference, needs LOS for best performance

Chandigarh University, the system respected social norms and reduced the number of mapping iterations to support safe navigation around humans [107]. Finally, Wang et al. (Figure 5E) focused on 3D navigation in uneven terrains using RGB-D cameras and an enhanced RRT algorithm. Their OctoMap-based framework distinguished between slopes and staircases, ensuring safe movement through cluttered and physically complex indoor spaces [104]. These case studies highlight Visual SLAM's adaptability from precise mapping and environmental sensing to socially intelligent and terrain-aware navigation, showcasing its transformative role in indoor robotics. Table VII provides a detailed comparative summary of various implementations of SLAM, outlining their domain of focus, strengths, shortcomings, techniques used, applications, and trends.

3.2.3. Comparative performance across scenarios

Other positioning technologies have been revised and will develop diverse systems suited for each one of the challenges specific to environmental types and applications. IMU, VLC, Infrared Systems, LiDAR, and Visual SLAM differ yet have different advantages and limits depending on the situation. Before selecting the appropriate solution for a specific use case, every technology must be assessed against position accuracy, cost-effectiveness, robustness, and scalability. Table VIII below provides a detailed comparison and contrast of these technologies, as well as their strengths and weaknesses in different settings, and illustrates the importance of both environmental conditions and application needs, along with system integration, to ensure the effectiveness of each positioning methodology.

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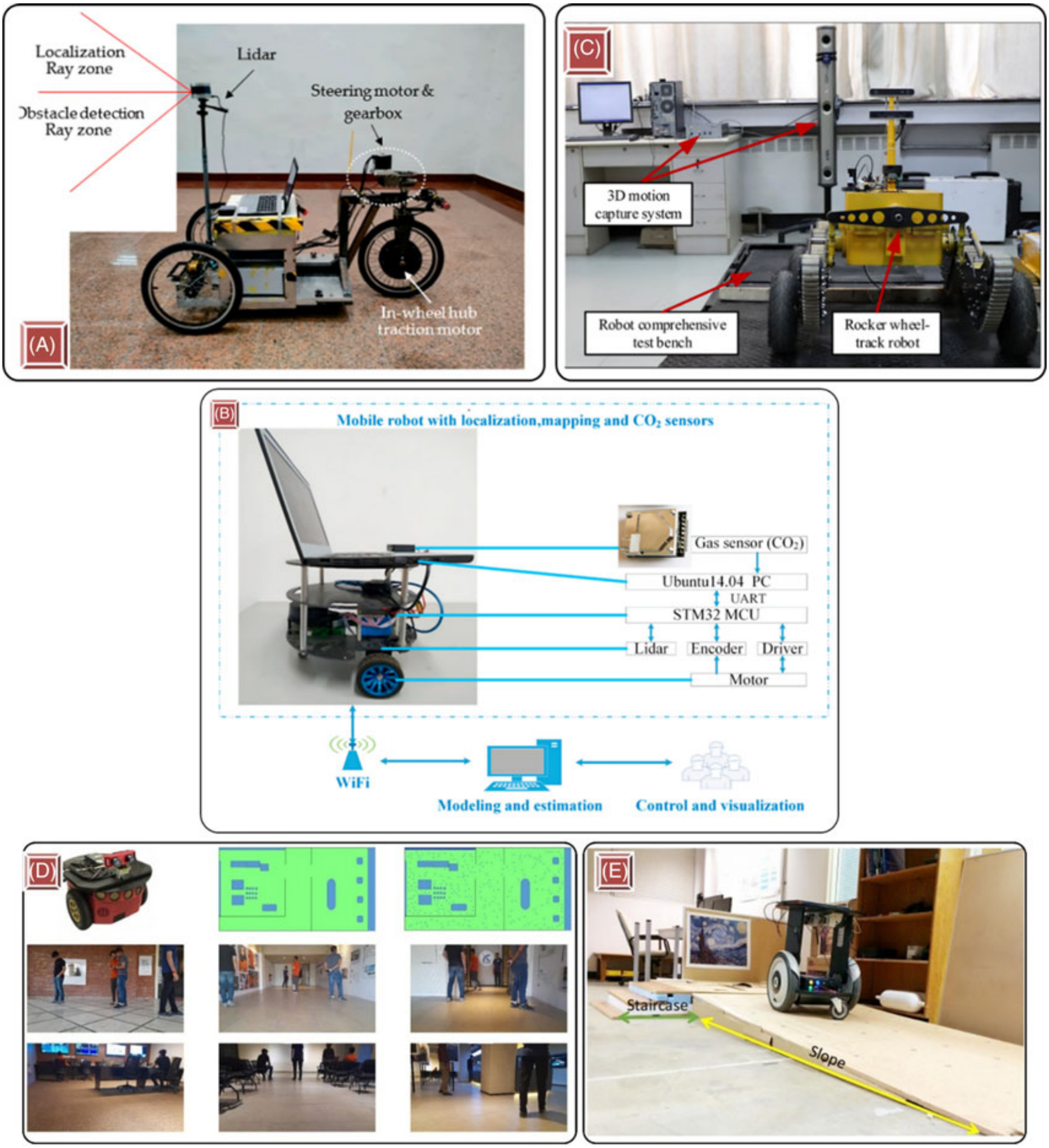

Figure 5. *(A) SLAM framework that relies exclusively on liDAR sensors for indoor mobile robot navigation, taken from ref. [100], copyright MDPI. (B) Indoor environmental monitoring, taken from ref. [105], copyright Elsevier. (C) STCM-SLAM for precise pose estimation, taken from ref. [106], copyright IEEE. (D) SLAM-based navigation systems for environments populated with humans, taken from ref. [107], copyright IEEE. (E) SLAM-based 3D OctoMap navigation system for complex 3D environments, taken from ref. [104], copyright MDPI.*

4. Radio frequency methods

First, RF methods have become essential for enabling wireless communication between robots and effective navigation. RF signals from Wi-Fi, Bluetooth, and RFID help robots locate objects, map environments, and keep connections in real time. Above all, such methods have proven efficient when

Table VII. *Summarizing key details like focus, strengths, limitations, key techniques, applications, and overarching trends.*

Ref. Nos.	Focus	Strengths	Limitations	Key techniques	Applications	Overarching trends
[91]	Range-only SLAM for mobile robots	It uses RSSI for distance estimation and is suitable for WSN integration. With prior node position knowledge, achieved an average localization error<1 m; reduced error to 0.5 m.	Noisy RSSI data; limited accuracy in complex environments.	Extended Kalman Filter (EKF) is a pre-processing filter for RSSI.	Surveillance and rescue operations using wireless sensor networks.	Focus on energy-efficient, adaptive localization methods in WSN environments.
[108]	Dynamic indoor navigation using SLAM and RL	Combines SLAM with reinforcement learning for dynamic obstacle avoidance. Improved path efficiency by 20%.	Requires significant computing resources; sensor limitations.	Kinect is used for mapping, and a rotary encoder is used for localization.	Assisting disabled individuals, delivery services, and domestic robots.	Emphasis on adaptability to dynamic and unstructured environments.
[109]	Multi-sensor fusion for indoor localization	Robust localization using ORB-SLAM, IMU, and wheel odometry. Achieved localization error of<5 cm in controlled environments	Challenges in low-light or high-speed scenarios; limited robustness under dynamic changes.	ORB-SLAM, multi-sensor fusion (IMU, odometry).	Indoor mobile robots, navigation in GPS-denied environments.	Multi-sensor fusion enhances localization accuracy and robustness.
[110]	Wi-Fi-based positioning with SLAM integration	Improved accuracy (by 40%) and cost-efficiency by leveraging existing Wi-Fi infrastructure.	Signal interference and environment dependency; limited robustness in low Wi-Fi density areas.	Wi-Fi fingerprinting, extended Viterbi algorithm, SLAM fusion.	Indoor localization, robot-based learning data collection.	Integration of ubiquitous Wi-Fi infrastructure with SLAM for localization.
[111]	PF-SLAM for dynamic indoor environments	Efficient navigation in dynamic environments with reduced computation and mechanical strain.	Susceptible to noise and computational challenges in large-scale scenarios.	Particle Filter SLAM, motion optimization.	Mobile robots in dynamic indoor settings, service robots.	Optimization of SLAM algorithms for dynamic environments with real-time adaptability.
[112]	Pseudo-GNSS/INS for indoor mapping	Provides GNSS-equivalent functionality in GNSS-denied areas; flexible integration with existing frameworks.	Computational complexity of post-processing; limited to indoor environments.	Probabilistic SLAM, LiDAR for sparse point cloud extraction.	Indoor mapping, unmanned ground vehicles, and high-precision navigation.	Transition from GNSS-dependent to GNSS-independent mapping technologies.
[113]	Path planning for indoor substations	A∗ for global paths, DWA for local paths; robust map creation with EKF-based sensor fusion.	Limited adaptation to moving obstacles; challenges in high-density environments.	A∗ algorithm, DWA, extended Kalman filter (EKF).	Indoor substations, robot-assisted maintenance.	Integration of multiple navigation and mapping methods for task-specific applications.
[114]	Autonomous navigation using SLAM under ROS	High precision map building; robust path planning.	Dependency on specific algorithms like A∗ and DWA.	Karto SLAM, A∗, and DWA algorithms.	Indoor navigation, robot automation.	Integration of ROS for effective autonomous navigation.
[115]	Drift-free visual SLAM with UWB technology	Reduced drift error by over 50%; better indoor accuracy.	Dependency on UWB infrastructure.	Visual SLAM, UWB integration, Extended Kalman Filter.	Smart factories, indoor localization.	Combining UWB with visual SLAM for drift reduction.
[116]	Positioning and navigation in industrial robots	High accuracy through optimized particle filter and Kalman filter fusion.	Challenges in low-light environments with visual SLAM.	Particle filter, Unscented Kalman filter, PSO optimization.	Industrial automation, precise navigation.	Combining multiple filters for robust industrial navigation.
[54]	LiDAR and IMU integrated navigation	High localization accuracy; resilience to signal occlusion.	High dependency on sensor fusion accuracy.	Voxel-SIFT, LiDAR, IMU, Kalman Filter.	Indoor mobile robots, sensor-integrated navigation.	Fusion of LiDAR and IMU for robust indoor positioning.
[117]	3D point cloud mapping with SLAM	Accurate 3D mapping with real-time registration.	Higher noise levels in dynamic conditions.	Hector SLAM, 3D points cloud registration.	Construction site mapping, dynamic environments.	Integration of SLAM for high-resolution 3D point cloud generation.
[118]	Comparison of SLAM technologies for indoor mapping	Centimeter-level mapping accuracy; evaluation of multiple SLAM systems.	Variation in accuracy is based on hardware configurations.	LiDAR, Matterport, and NAVIS systems comparison.	Indoor mapping, technology evaluation.	Benchmarking multiple SLAM approaches for specific applications.
[119]	Development of mobile robot SLAM using ROS	Ease of implementation with ROS; effective for tracked robots.	Limited to the ROS ecosystem and specific hardware setups.	Monte Carlo localization, ROS framework.	Education, indoor navigation.	Utilizing ROS for accessible and modular SLAM development.
[120]	Real-time visual SLAM with GPS for outdoor robots	Integration of GPS reduces drift and improves scale estimation.	Sensitive to GPS signal quality in obstructed areas.	Visual SLAM, GPS fusion, and graph optimization.	Outdoor robot navigation, augmented reality.	Hybrid SLAM approaches are robust for outdoor applications.

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Table VIII. *Provides a comparative performance analysis of various positioning technologies [28, 39, 40, 48].*

Technology	Position accuracy	Cost-efficiency	Robustness	Scalability
Inertial Measurement Units (IMU)	Moderate: Prone to drift over time; accuracy degrades without external corrections.	High: Affordable for standalone systems, but increases with additional integration.	Moderate: Reliable in GPS-denied areas but accumulates errors without correction.	High: Easily integrate with other systems like GPS or SLAM.
Visible Light Communication (VLC)	High: Achieves sub-meter accuracy in well-lit conditions with sufficient LEDs.	Moderate: Requires specialized infrastructure; costs increase with scalability.	Low: Sensitive to environmental lighting conditions and line-of-sight issues.	Moderate: Scales effectively in controlled environments but are limited in dynamic settings.
Infrared Systems	Moderate: Effective for short-range indoor positioning, typically accurate within 1-2 m.	Moderate to High: Affordable but dependent on sensors and infrastructure.	Moderate: Affected by environmental interference and requires a line of sight.	Low to Moderate: Suitable for small-scale indoor setups, challenging for large-scale deployments.
Light Detection and Ranging (LiDAR)	Very High: Achieves centimeter-level accuracy in structured environments.	Low to Moderate: Expensive hardware, costs increase with resolution and range.	High: Robust against environmental changes but limited in low-light or featureless areas.	Moderate: Scales well in structured indoor or outdoor environments but is costly.
Visual Simultaneous Localization and Mapping (Visual SLAM)	High: Accurate in feature-rich environments, sensitive to lighting and textures.	Moderate: Cost depends on the camera type (monocular, stereo, RGB-D).	Moderate: Prone to motion blur, low-light issues, and challenges in texture-less spaces.	High: Adaptable to various settings with proper sensor integration and algorithms.

applying other traditional sensors, such as cameras or LiDAR, becomes impossible. Based on the RF technology, robots can perform seamlessly in complex indoor environments [28].

4.1. Wi-fi-based indoor mobile robots

Wi-Fi-based indoor mobile robots depend on wireless internet signals for navigating, localizing, and communicating inside indoor spaces. The robots use a triangulation technique called Wi-Fi signal triangulation or fingerprinting to anchor their position [29]. To determine its position, the robot integrates the Received Signal Strength Indicator (RSSI) of several Wi-Fi access points in the building. By matching these measurements with a map of the environment built before, the robot can estimate its actual position

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with reasonable accuracy during calibration. Apart from this, Wi-Fi plays a vital role in real-time communication: connected to a Wi-Fi network, the robot will send and receive updates about itself, readings from its sensors, or even instructions. This type of communication allows the operators to control the robot from a distance via another device. It enables two or more robots of other types to cooperate as a group, sharing information in real time. Wi-Fi also allows connecting to the cloud, accessing advanced computing resources the robot can use, or sharing information for other purposes, such as complex decision-making or machine learning [121, 122].

Indoor localization has witnessed transformative progress by integrating Wi-Fi, machine learning, and robotics, tackling long-standing accuracy, adaptability, and scalability challenges. Shu et al. (Figure 6A) proposed a multimodal localization approach combining 3D point cloud data with Wi-Fi fingerprinting to estimate 6-DoF robot poses. By reducing search complexity and mitigating noise in large-scale settings (650+ million points), their fusion method proves highly effective in intricate indoor environments [123]. Furthermore, Ayyalasomayajula et al. (Figure 6B) proposed DLoc utilizing deep learning in combination with MapFind, a self-mapping platform. This combination can allow for the creation of a large-scale, labeled dataset from mapping and deeper modeling, improving accuracy and reducing manual input while also being able to tolerate multipath errors and sparse maps [124]. Turning to passive systems, Chan et al. (Figure 6C) created an entropy-optimized passive Wi-Fi localization system using genetic algorithms to evaluate optimal placement of Wi-Fi sniffers. Their system achieved 2.2-m accuracy while providing a cheaper and device-free option for tracking in real time [125]. To improve data collection, Lin et al. (Figure 6D) presented a hybrid deep learning approach using supervised, semi-supervised, and unsupervised learning with robot-collected RSSI data, enabling incremental learning and adaptability in obstacle-rich settings [126]. Finally, Kharmeh et al. (Figure 6E) presented a low-cost robotic solution for generating automatic 3D Wi-Fi radio maps. Using a combination of SLAM and data fusion, the scalable and low-cost architecture facilitates automatic collection and mapping of Wi-Fi radio maps at a significant reduction in labor consumption and energy use when deploying to larger scales [127]. Together, these studies reflect how multimodal integration, AI, and robotic automation reshape indoor localization systems, making them more precise, scalable, and adaptive to dynamic environments. Table IX consolidates major prospects into equally compelling trends, driving innovations in this field.

4.2. Radio frequency identification (RFID)-based indoor mobile robots

RFID-based indoor mobile robots are used to navigate and perform tasks within specific indoor fields or environments with Radio Frequency Identification (RFID) technology. In this system, RFID tags are placed at critical, specific locations as markers or waypoints that contain unique identification information for the robot to read from an RFID reader. The robot scans these tags while moving to determine where it is and verify that it is going to the right place. The RFID reader used by the robot emits signals to detect nearby tags, and the information is processed using other sensors, such as cameras or ultrasonics, to avoid obstacles and issue commands. This method is very efficient for the purposes of tracking the robot's position and guiding its movement, without the use of GPS, for suitable indoor applications, like warehouses, hospitals, and offices [138, 139]. Building on the advancements in indoor navigation, Demiral et al. [140], presented a modular RFID-guided robot prototype for structured environments. Using strategically placed RFID tags and auxiliary sensors such as gyros and ultrasonic detectors, the system enables autonomous pathfinding through shortest-path algorithms, as shown in Figure 7 (A). This practical, cost-effective solution sets a foundation for more advanced navigation systems in emergency and service applications. Extending these principles, Wu et al. [141], developed a standalone RFID-based navigation method using phase-difference modeling (shown in Figure 7 (B)). This innovative approach eliminates the need for additional sensors or reference tags, achieving precise localization with a distance accuracy of 4.04 cm, showcasing RFID's potential for unstructured navigation. Taking precision navigation further, Kammel et al. [142] introduced a hybrid system that integrates UHF RFID and odometry for centimeter-level localization, shown in Figure 7 (C). This system proves its robustness

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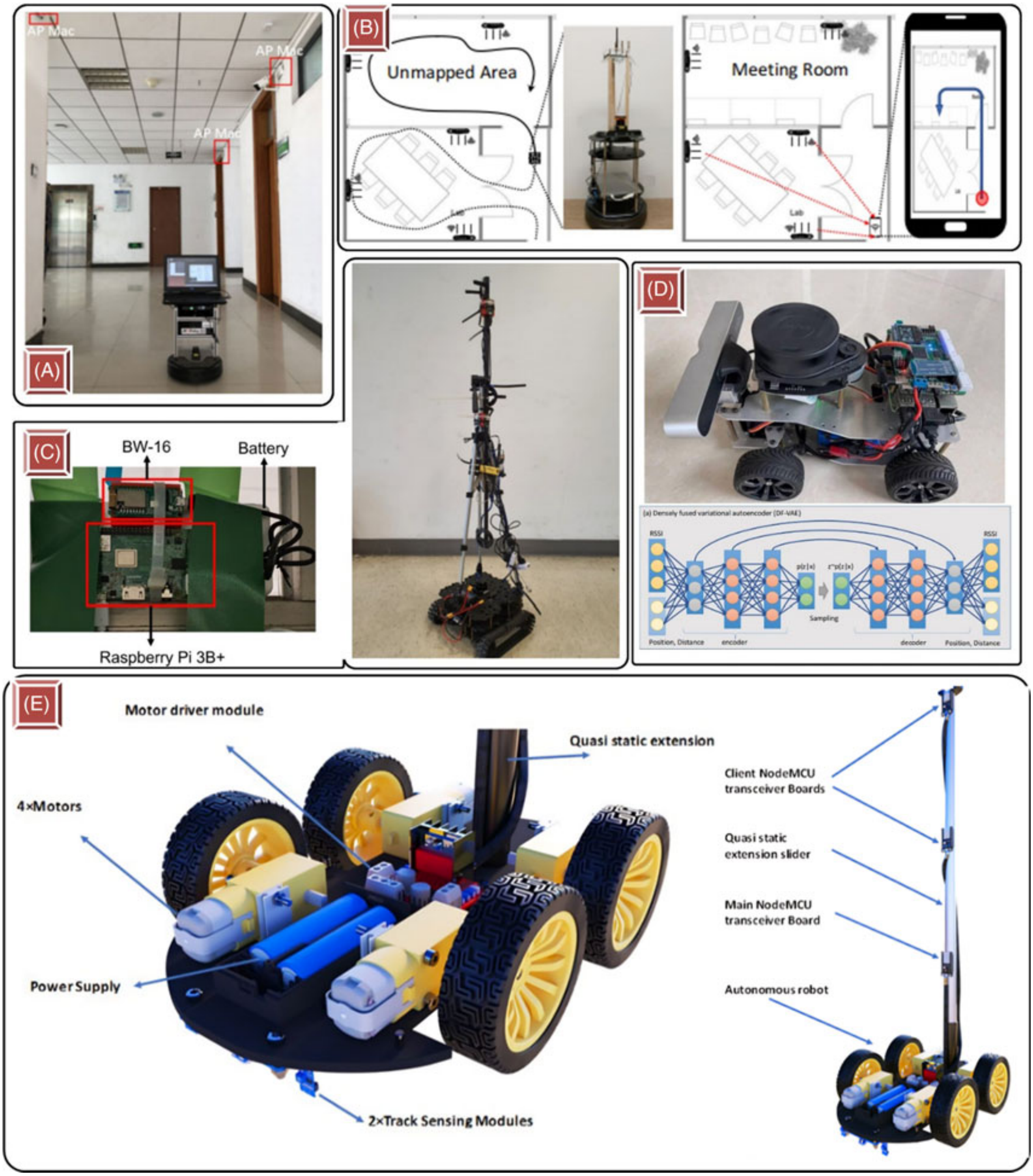

Figure 6. *(A) A multimodal approach combining 3D point clouds and Wi-Fi signals to achieve pose estimation for mobile robots was taken from ref. [123], copyright IEEE. (B) Deep learning-based system that pairs neural networks with MapFind, an autonomous mapping platform, taken from ref. [124]. (C) Wi-Fi-based indoor positioning system, taken from ref. [125], copyright MDPI. (D) wi-fi RSSI-based indoor Robots for obstacle-rich environments, taken from ref. [126], copyright MDPI. (E) 3D Wi-Fi localization using low-cost robots for large-scale deployments, taken from ref. [127], copyright MDPI.*

in warehouse environments by addressing odometry drift and multipath interference through iterative Kalman filtering. Building on this, Shangguan and Jamieson [143], tackled sorting closely spaced RFID-tagged items in dense environments. Their MobiTagbot system leverages synthetic aperture radar techniques to achieve nearly 100% accuracy, making it a breakthrough for libraries and supply chains, as shown in Figure 7 (D). Similarly, DiGiampaolo and Martinelli [144], focused on robotic localization in shelves (shown in Figure 7 (E)), combining odometry and RFID signal analysis to achieve high precision (∼10 cm error) in cluttered scenarios like metallic storage racks. Beyond single-robot applications, cooperative approaches have been explored. Seco and Jiménez [145] proposed a smartphone-based localization system that integrates RFID tags, pedestrian dead reckoning (PDR), and map data, reducing errors from 6.1 m to 1.6 m through collaborative tracking. This complements the low-cost HF RFID system by Mi and Takahashi [146], which optimizes sparse tag placement and achieves millimeter-level accuracy, broadening the use cases for service robots in public facilities. Meanwhile, Ye and Peng [147] improved WiFi-based fingerprinting for robot navigation by refining grid-based points and adaptive correction, achieving accuracy within 0.4 m for dynamic indoor tasks. Closing the loop, Da Mota et al. [148] integrated Petri nets with RFID tags for structured navigation in labyrinth-like spaces, while Kassim et al. [149], extended RFID's reach to assist visually impaired individuals, combining tactile paving and digital compasses for inclusive indoor mobility. These studies illustrate RFID's versatility, spanning precision robotics, collaborative systems, and accessible technologies. The diverse applications and innovations in RFID-based indoor robotics demonstrate the adaptability and precision of this technology across various fields. The advancements highlighted above showcase various approaches tailored for specific use cases, from structured navigation to unstructured environments, and single-robot systems to collaborative networks. Table X comprehensively compares the reviewed studies to illustrate these findings further, detailing their focus, strengths, limitations, key techniques, and applications.

4.3. Ultra-wideband (UWB) and bluetooth-based indoor mobile robots

UWB and Bluetooth-based indoor mobile robots use advanced wireless technologies to determine their location and navigate within indoor spaces. UWB operates by sending very short radio pulses across a wide frequency range. These pulses travel to multiple fixed anchors in the environment, and the time for the signal to travel to and from them is measured. Using this "time-of-flight" data, the robot can calculate its precise position with high accuracy, often within a few centimeters. On the other hand, Bluetooth technology, particularly Bluetooth Low Energy (BLE), works by detecting signal strength (RSSI) from beacons placed around the area. The robot can estimate its position by analyzing these signal strengths and sometimes combining them with other methods like triangulation [151, 152]. Together, these technologies can complement each other. UWB provides high precision, ideal for tasks requiring fine control, while Bluetooth offers cost-effective and energy-efficient positioning for broader navigation. Using these systems, the robot can map its surroundings, avoid obstacles, and move efficiently to complete its tasks in warehouses, hospitals, or smart homes.

Recent developments in indoor localization have demonstrated the effectiveness of combining multiple sensing approaches to alleviate some of the problems of accuracy, robustness, and adaptability. A noteworthy example of this is in the work of Kok et al. [153], which presented a tightly coupled UWB-IMU fusion system through a maximum a posteriori (MAP) formulation. Their approach uses a heavily tailed asymmetric distribution to filter UWB data for outliers, indicating improved pose estimation compared to optical tracking, even in a non-line-of-sight (NLOS) tracking condition. Expanding on this, Yao et al. [154], leveraged an Extended Kalman Filter (EKF) to fuse UWB and IMU data, effectively addressing inertial drift and UWB multipath effects. Their system delivered over 100% improvement in accuracy compared to traditional UWB-only approaches, proving the synergy of complementary technologies in real-world lab and simulation environments. Investigating Bluetooth-based solutions, Weinmann and Simske [155], Introduced a Bluetooth 5.1 Angle of Arrival (AoA) system for autonomous robots and demonstrated a 0.12-m mean localization accuracy through beacon-based corrections. The possibility of utilizing this in scenarios like fire rescue and capturing objects under harsh indoor conditions is promising. Furthering the use of UWB, Juston and Norris [156] developed an ad hoc mesh network localization system for mobile robots. Using UWB and odometry with an unscented Kalman filter, the decentralized setup enabled real-time adaptability and dynamic environment compatibility, allowing

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Table IX. *Comparative analysis for wi-fi-based indoor localization techniques.*

Ref. Nos.	Focus	Strengths	Limitations	Key techniques	Applications	Overarching trends
[128]	Cloudlet-based cloud system for positioning	Real-time autonomous cart positioning, seamless handover	Limited to Wi-Fi coverage environments	Cloudlet-based architecture, RSSI	Factory automation, personnel, and asset tracking	Edge computing integration with indoor Wi-Fi systems
[129]	UWB and Wi-Fi integration for indoor positioning	High precision, robust against environmental interferences	Higher cost of UWB systems	Differential Wi-Fi, Multi-sensor Fusion	Emergency responder navigation, parking models	Fusion of diverse localization technologies for robust solutions
[130]	Augmenting visual SLAM with Wi-Fi sensing	Improved SLAM accuracy by 11%, reduced computational complexity	Reliance on high-quality Wi-Fi infrastructure	Integration of Wi-Fi RSSI with visual SLAM	Robotics in navigation, augmented reality	Combining visual and Wi-Fi data for enhanced indoor positioning
[131]	Map/INS/Wi-Fi integrated system	Enhanced accuracy through cascaded filtering, with low computational overhead	Dependency on precise pre-existing maps	Kalman Filter, Map Matching	Mobile device-based location services (airports, museums)	Multi-source data integration for continuous navigation
[132]	Wi-Fi radio map construction with smartphones	Cost-efficient solution using existing consumer devices	Manual site surveys remain time-consuming	Factor Graph Optimization, k-Nearest Neighbor	Public spaces (malls, stations)	Affordable, high-accuracy solutions utilizing prevalent consumer devices
[133]	Wi-Fi-based mobile robot positioning	Effective in noisy environments, robust against dynamic changes	Vulnerable to RSSI fluctuations	RPCA-ELM, Wi-Fi Fingerprinting	Industrial robotics, autonomous systems	Enhancing robustness in real-world dynamic conditions
[134]	Flexible Wi-Fi communication in robots	Addresses coverage and latency issues in industrial setups	Scalability limitations with mesh networks	Mesh Network, Mixed Architecture	Industrial logistics, automated guided vehicles (AGVs)	Industry 4.0 emphasizes scalable and reliable communication for mobile robotics
[135]	Multi-sensor indoor localization for biped robots	Robust in harsh industrial environments, adaptive to different conditions	Complex implementation, high cost of hardware	Cellular Automata Particle Filtering, Multi-Sensor Fusion	Industrial robotics, biped robot localization	Multi-sensor fusion for reliable localization in dynamic industrial environments
[136]	Indoor positioning system using Wi-Fi and BLE in harsh environments	Combines coarse Wi-Fi and fine BLE positioning, suitable for noisy environments	Limited BLE beacon density, multipath fading issues	Wi-Fi and BLE Fusion, Weighted k-NN	Public transportation stations, smart cities	Hybrid solutions combining Wi-Fi and BLE for robust indoor positioning
[137]	Fusion of RSSI and magnetometer fingerprints for 2D positioning	Improved accuracy in high variance magnetic environments, lightweight algorithm	Reliance on environmental magnetic field variability	RSSI-Magnetometer Fusion, Multilayer Perceptron	Mobile robot navigation in industrial settings	Sensor fusion for enhancing accuracy in challenging indoor environments

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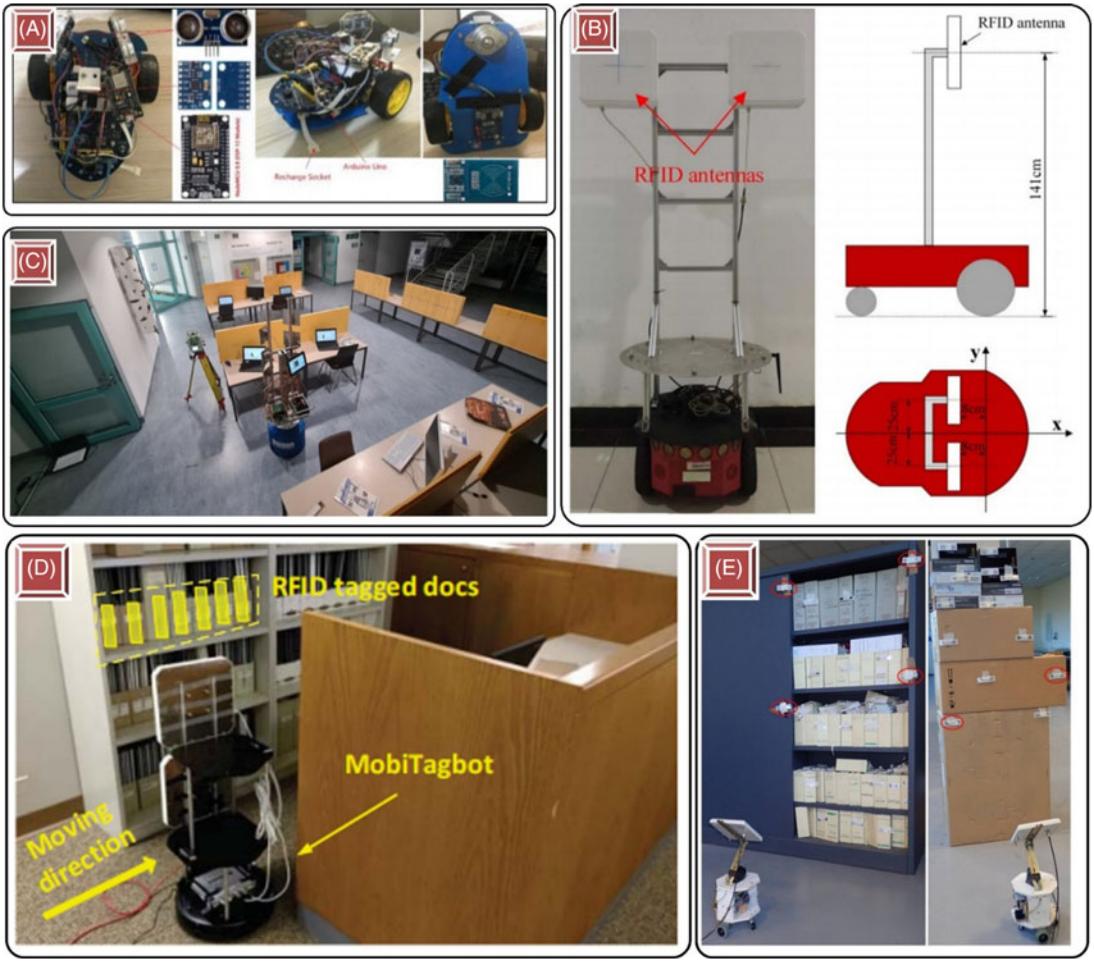

Figure 7. *(A) RFID-guided robot prototype for structured environments, taken from ref. [140]. (B) RFID-based standalone navigation method, taken from ref. [141], copyright IEEE. (C) RFID and odometry for centimeter-level localization robustness in warehouse environments, taken from ref. [142], copyright IEEE. (D) RFID-tagged items in dense environments, taken from ref. [143]. (E) RFID-based indoor robot for detecting items localized in shelves, taken from ref. [144], copyright IEEE.*

mobile agents to self-correct and synchronize locations without fixed infrastructure. In a unique application, Naheem et al. [156] created a lighter-than-air helium robot with a wearable UWB sensor for user-following and intent detection. The interactive system could successfully track pose in open indoor spaces, providing opportunities for applications in entertainment, guidance, and user awareness. These case studies illustrate the versatility of UWB, IMU, and Bluetooth technologies, especially when used with advanced filtering and control algorithms. They offer a promising path toward scalable, accurate, and adaptive indoor positioning systems, catering to diverse domains from robotics to human-interactive applications.

These case studies collectively demonstrate how indoor positioning technologies, whether based on UWB, BLE, or hybrid sensor fusion, are evolving to meet the complex demands of real-world applications. From handling non-line-of-sight conditions to enabling real-time collaboration among mobile agents, these systems reflect modern IPS research's promise and intricacies. To further contextualize the capabilities and trade-offs of various radio frequency-based IPS technologies, Table XI below presents a comparative analysis of commonly used RF methods. This table evaluates each technology across

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Table X. *Comparison of RFID-related research papers.*

Ref. Nos.	Focus	Strengths	Limitations	Key techniques	Applications	Overarching trends
[148]	Localization and navigation using Petri Nets in indoor environments	Accurate decision-making via Petri Nets; Suitable for structured environments	Depends heavily on structured paths and specific layouts	Petri Net dynamics, RFID-based localization	Industrial and educational robot navigation	Emphasis on combining RFID with advanced decision-making frameworks
[146]	HF-Band RFID system for indoor mobile robot self-localization	Robust low-cost localization; uses fewer readers and tags	Performance depends on optimal tag-reader arrangement	Monte Carlo Localization, likelihood modeling	Indoor service robots in public facilities	Cost-efficiency, robustness in localization with fewer resources
[147]	WiFi fingerprint positioning for indoor navigation	Improved WiFi localization, 0.4m accuracy improvement, navigation error<0.8m	Still limited by signal inconsistencies and real-time challenges	WiFi signal standardization, adaptive WKNN algorithm	Indoor navigation in complex environments	Enhanced signal processing for indoor environments
[149]	RFID and digital compass for visually impaired navigation	Enhances navigation for the visually impaired; accurate compass calibration	Limited scalability; requires tactile paving for effectiveness	Digital compass, voice guidance, passive RFID	Navigation aid for the visually impaired in public spaces	Accessibility enhancements via RFID navigation systems
[150]	Indoor robot navigation with RFID and shortest path algorithms	Autonomous navigation; integration with gyro and pathfinding algorithms	Limited RFID range ($\sim$5 cm); dependent on shortest-path algorithm	Shortest path algorithm, Arduino, gyro sensors	Emergency navigation, indoor logistics	Integration of RFID with autonomous robotics
[145]	Smartphone-based cooperative localization using RFID	Improved cooperative localization accuracy to 1.6m (with map)	Dependent on the density of anchor nodes and PDR quality	Particle filter, cooperative Bayesian localization	Personal and group indoor tracking	Collaborative methods for improving indoor positioning

essential performance metrics such as accuracy, scalability, cost, latency, robustness, and environmental suitability, offering a concise yet informative summary for readers and practitioners exploring optimal IPS design strategies.

5. Research gaps and future directions

IPS are critical to enabling autonomous mobile robots to navigate and perform tasks effectively in complex indoor environments. While significant advancements have been made, many challenges hinder the full realization of robust and scalable IPS solutions. This section identifies some key research gaps and suggests some actionable solutions toward addressing them, paving the way for future innovations. IPS are critical to enabling autonomous mobile robots to navigate and perform tasks effectively in complex indoor environments. While many advancements have been made, several challenges will keep IPS

Table XI. *Comparative analysis of RF-based IPS methods [27, 29, 42, 155].*

Feature	**Wi-Fi**	**Bluetooth low energy**	**Ultra-wideband**	**ZigBee**	**RFID**
Accuracy	Low to Medium (1–5 m)	Medium (1–3 m)	High (< 30 cm)	Low (> 5 m)	Low to Medium (1–4 m)
Scalability	High	High	Medium	Medium	High
Cost	Low	Low	High	Low	Low
Latency	Medium	Low	Low	Low	Low
Robustness	Medium	Low to Medium	High	Low	Medium
Environmental suitability	Indoor/outdoor, affected by interference	Indoors, susceptible to interference and signal drop	Indoor, robust in cluttered environments	Short-range indoors, suffers in noisy RF environments	Indoor, suitable for access control and asset tracking
Advantages	Widely available infrastructure, good range	Low power consumption, cost-effective	High precision, robust to multipath interference	Low power, mesh networking capable	Low-cost, passive tags don't require power
Disadvantages	Susceptible to signal fluctuation and interference	Limited range, sensitive to obstacles	High cost, complex hardware	Lower accuracy, not suitable for large-scale precision tasks	Limited range and accuracy require a line-of-sight for best performance

solutions from being robust and scalable. In this section, research gaps will be identified, and potential solutions will be proposed.

5.1. Signal interference and multipath effects – deep learning-based mitigation strategies

IPS, especially those that rely on RF with Wi-Fi, Bluetooth, and UWB as the fidelity, will face two basic radio issues: signal interference and multipath effects. These challenges arise due to the inherent nature of indoor environments, which are typically filled with metallic objects, thick walls, moving people, and other electromagnetic barriers. When the RF signals meet obstructions, they will reflect, diffract, or scatter (or in combination), leading to multipath. In this process, signals reach the receiver through multiple paths with varying delays and attenuations, distorting the original signal. Additionally, electromagnetic interference from co-located devices such as smartphones, microwave ovens, routers, and even other localization systems can further degrade signal quality and reliability [28, 157]. In addition, these interferences vary with floor plans, materials, and ambient conditions; it is nearly impossible to develop a universal interference mitigation technique that is robust across all use cases. Therefore, IPS systems often require environment-specific calibration, limiting generalizability and plug-and-play deployment.

The degree to which these signal distortions jeopardize localization accuracy is significant. Specifically, multipath propagation can cause incorrect distance estimation (e.g., delayed paths being incorrectly registered as part of the travel distance). On the same note, the variable signal strengths caused by interference produce variable RSSI (Received Signal Strength Indicator) readings on which fingerprinting techniques rely. These challenges are particularly severe in densely populated or mission-critical scenarios, like hospitals, warehouses, and manufacturing robots, in which robots must navigate

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accurately and promptly make decisions. In these cases, small errors in location estimation can mean failures, inefficiencies, or risks to safety. Conventional signal processing methods have been widely employed. Techniques like Kalman and particle filters smooth noisy signal trajectories by predicting and correcting the robot's position over time. Channel State Information (CSI) filtering aims to acquire a stable reconstructed signal component from noisy multipath conditions. Meanwhile, frequency-hopping spread spectrum techniques exploit several frequencies to avoid persistent interference. Despite these advantages, these model-based approaches rely on relatively static conditions. Whether model-based or not, they can't generalize or become flexible in highly dynamic or non-linear indoor spaces, leading to limited use over extended time [158].

To overcome these shortcomings, DL has obvious potential for real-time signal correction and multipath mitigation for indoor positioning systems. Moreover, DL models are data-driven, meaning they can learn complex and nonlinear relationships between noisy input signals (such as raw CSI, ToA, and phase differences) and true position outputs. They can work with high-dimensional input spaces and be trained to find patterns in signal distortion that were impossible to model explicitly. More importantly, DL systems are flexible and can continually adapt to new environments or conditions. This unique property makes them perfectly suited to dynamic indoor spaces where conventional models ultimately fail. The task of performing denoising, feature extraction, classification, and regression together makes robust end-to-end positioning pipelines possible. The following Table XII summarizes the relative use of the different DL models for signal correction and multipath mitigation [159, 160].

In the future, DL can enable many new opportunities to improve indoor positioning systems. For example, we could consider different types of deep learning frameworks, using CNNs to understand the shape of signals and LSTMs to capture how those signals may change over time. This collaborative modeling may yield more accurate and reliable positioning. Another challenge will be to shrink and accelerate the models' size sufficiently so that they can be operated directly on a robot or other small device without direct access to a cloud data server. While this would put decision-making on the spot for a robot, it would not eliminate the need for a sizeable data store to learn from in the first place. Furthermore, it is tough to collect enough training data in many environments. Therefore, research in this area will explore ways to reuse models trained in one building and use that model in a new space (just as people quickly adjust to the layout of unfamiliar spaces). Lastly, creating data-sharing datasets and benchmarking tools would allow researchers to compare and assess existing systems and accelerate progress fairly. With all of these discussions and developments, we will undoubtedly see more applications of deep learning to ensure indoor navigation technology will be more innovative, quicker, and reliable than ever [163].

5.2. Environmental variability and dynamic obstacles

The ever-changing nature of an indoor environment – a moving set of people, furniture, and equipment – challenges the ability of IPS to achieve suitably consistent accuracy. Many systems cannot respond to rapid environmental changes, degrading their localization and navigation performance. Real-time scene understanding that accounts for semantic mapping and identifying dynamic objects using convolutional neural networks with reinforcement learning may ameliorate the issues IPS systems face. Multi-sensor fusion techniques integrating vision systems, LiDAR, and inertial measurement units can provide more reliable localization. Predictive path planning algorithms can communicate with the navigation system to dynamically adjust navigation strategies while overcoming obstacles in real time [5].

5.3. Scalability and deployment challenges

Scalability, in the context of IPS, can be understood as how an IPS continues to perform when deployed in large spaces, populous environments, or different building contexts, without losing accuracy, speed, or dependability. Though research has significantly progressed the IPS technological developments, scaling

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Table XII. *Deep learning models for signal correction and multipath mitigation [161, 162].*

Model	Application	Working mechanism	Strengths	Limitations
CNN (Convolutional Neural Network)	CSI or spectrogram analysis	Treats signal data as images to learn spatial features and suppress multipath artifacts	Excellent spatial feature extraction; good for static environments	Needs large,, labeled datasets; less effective in capturing time series
RNN / LSTM	Temporal modeling of RSSI, ToA	Captures time-dependent variations in sequential signal inputs	Effective for dynamic path estimation and real-time tracking	Training can be slow, prone to vanishing gradients
Transformer	Complex environments with long dependencies	Uses self-attention to capture global dependencies across signal sequences	Scales well; interpretable attention mechanisms; state-of-the-art accuracy	Computationally heavy; requires extensive data
Autoencoder/ denoising autoencoder	Signal denoising	Learns latent clean signal representations and reconstructs them	Useful for unsupervised learning and data compression	May retain artifacts if not properly tuned
GAN (Generative Adversarial Network)	Signal simulation and augmentation	Generates synthetic clean data from noisy samples using adversarial training	Helps in data scarcity and generalization	Difficult to train; unstable convergence
Graph Neural Network	Node-based IPS with spatial awareness	Learns on graphs where nodes represent anchors or access points	Captures relationships in non-Euclidean space; suitable for multi-device localization	Requires graph structure and node connectivity data

deployments in practice remains a frustrating barrier. One primary reason is that most IPS technologies do not function the same way everywhere. For instance, a system tuned to work in a hospital with long corridors and wide-open wards will not work the same in a shopping mall with glass storefronts, multiple floors, and thick walls. IPS solutions are frequently based on specific layouts or infrastructure (placing sensors, anchors, beacons, just the right way). However, in the real world, every single building is different, so each configuration needs to be manually tuned, and that is just not feasible on such a large scale [164].

Cost and complexity are also issues. High-accuracy systems like LiDAR or radar can yield good results, but these systems can be costly, power-hungry, and bulky. Perhaps these systems are fine for research labs or high-budget projects, but they are not practical for typical environments like schools, retail stores, or homes. Even more "affordable" solutions like Bluetooth or infrared sensors can be unreliable in crowded, noisy environments or if other devices occupy the same frequency. Finally, there is the matter of computational load and real-time performance. Determining precise location and movement (some IPS functions) requires a lot of processing. We can send that data to the cloud, but it doesn't just require a stable internet connection, and it causes latency. Even with an edge computing approach, we

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have to find the right hardware to process the data on the device. The cost may be a concern, plus it drains their battery life; this is especially problematic for small robots or mobile sensors. The use of inexpensive sensors, such as RGB-D cameras or passive infrared sensors, even as a concept, isn't guaranteed to solve the problem either. Although these devices may be cheaper, they may not provide reliable accuracy, for example, in conditions where lighting changes, dynamic motion with people walking through the scene, or in a scene with many furniture or structural occlusions [165, 166].

Interoperability is another real and important bottleneck. IPS offerings from various vendors often don't play nicely together [167]. Because of this, it's challenging to construct a cohesive system across a whole campus or a smart building. It's like mixing up puzzle pieces from different boxes without common standards. So, with all the development and research, why haven't we solved this? IPS is not just about a clever algorithm but about making sense of problems that cross physical space and boundaries, hardware, human behaviors, financial constraints, and privacy laws. And all of this varies significantly by location. Nonetheless, progress has been made. One avenue of exploration is with the use of cloud-edge hybrid models (where processing is done on-device, and heavier computation is offloaded to the cloud); another is in modular system design, where different functions (for example mapping, tracking, storage) can be tailor-fit to a specific environment; another is with systems that self-calibrate, tools that automate installation, or redundant sensors, which all seek to reduce the workload of installation. Regarding it, scalability within IPS is not a technological problem but a contextually bound, real-world problem. Finding a solution will take more than better hardware or more innovative software; it requires building systems that are flexible, cost-effective, easy to deploy, and change, resilient systems across an unlimited number of unique and changing indoor spaces [5].

5.4. Accuracy in low-light and texture-less environments

Visual-based IPS has difficulty supporting SLAM algorithms in environments where lighting is constrained and distinctive visual features are lacking. Such hindrances substantially restrict the range of applicability of IPS in various areas, such as warehouses or tunnels. Enriched sensors, like infrared cameras integrated with thermal imaging, can enhance the operability of vision-based systems in situations of poor light. Generative adversarial networks could enhance image quality and extract features from texture-less areas. Combining visible light communication with infrared technology should also assist in increasing positioning accuracy in environments where visual identification is demanding [168, 169].

5.5. Long-term autonomy and adaptability

Most IPS solutions lack the ability to adapt to long-term changes in the environment, such as structural modifications or sensor degradation. This results in reduced reliability and increased maintenance requirements. Self-learning algorithms that continuously adapt to evolving environmental conditions can address these challenges. Autonomous map updating systems can integrate new data into existing maps without manual intervention. Incorporating redundancy mechanisms in sensor systems can ensure robustness against individual sensor failures [170].

5.6. Ethical and privacy concerns

IPS are quickly becoming part of every setting, from hospitals to factories, offices, and homes – essentially every place that should protect privacy. As these systems advance with AI and machine learning capabilities, we must consider their ethical privacy issues with the same level of care as their technical abilities. This section explores practical privacy risks, ethical obligations, and challenges with advanced methodologies such as federated learning (FL) when working with IPS-driven robotics.

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5.6.1. Privacy risks in sensitive environments

IPS solutions and their relevance to health, health care, elder care, and workplaces usually rely on real-time location information from people or mobile agents. Often, the intent is safety (or the effort to plan for things, like dispatching a robot to someone to refill supplies or, more simply, tracking what a nurse is doing). Nevertheless, data that monitors people continuously becomes a surveillance concern depending on the context and situation in which the data is being collected. To illustrate this in context: In elder care homes, monitoring a patient's movements in the event of a fall is beneficial; however, if monitoring is done without a straightforward process, transparency, options, or communication, there are ethical issues. Furthermore, assessing location information that could be misinterpreted, misused, or leaked into the real world can have serious ramifications. Some examples would include Stalking or harassment based on location, Revelation of employee habits (in the workplace), engaging with fixes, implementing improvements, and saving during a time-sensitive procedure, while being tracked by a competitor in another organization who wants to see how you behave, etc. These are a few situations that underscore the need for end-to-end encryption of data as a best practice, not only regarding the transfer of data but also after you have collected the data, as a best practice, to offer sustainability of your ethical commitment and confidence in data security to those represented [171, 172].

5.6.2. Ethical responsibility and informed consent

Many IPS deployments experience what could be described as "invisible surveillance." For example, individuals under surveillance do not necessarily know: (1) their location data is being recorded, (2) by whom it is being recorded, (3) how long it will be stored, and (4) if it can be deleted. Furthermore, a lengthy privacy policy document cannot bury proper informed consent. Having in-app notifications in the moment, using very simple language, and allowing them to opt in/ opt out is necessary to facilitate informed consent. Transparency and trust can also be achieved by giving users a dashboard or an app to allow them to control their consent. An example from healthcare: if a patient were to walk into a hospital that uses an IPS for navigation and safety purposes, a kiosk at the entrance or a user wristband with an app could inform the patient about the data that is going to be collected from them, and they can even control it. These micro-consent formats allow people to consent and have greater congruency with global data protection regulations [173, 174].

5.6.3. AI bias and fairness in IPS

AI-ML-powered IPS could mistakenly introduce bias, both in coverage and in accuracy. For example, a model-trained imitative of western hospital use in western hospital environments may suffer when used in hospitals in India and Japan, with different physical designs and layouts for rooms and hallways. This could create bad outcomes such as wrongly routed robots, poor localization performance, and a higher rate of errors for certain populations or geographical locations. Bias could be further compounded when utilizing historical data that reflects previously existing systemic biases. As such, the ethical design of AI in IPS must focus on utilizing diverse training data in its use cases and consider fairness criteria. Furthermore, algorithms should routinely be audited for bias and periodically retrained using new balanced datasets that represent inclusivity of geography, demographics, and physical layout of the built environment [20, 175, 176].

5.6.4. Advanced privacy-preserving techniques

Modern privacy engineering offers several promising technology options that can help organizations ensure the privacy of IPS data. The most relevant examples are: (1) Differential Privacy: introduces mathematical noise into datasets so that aggregate patterns can be identified but individuals cannot be identified; (2) Homomorphic Encryption: allows for computations to occur while the data is encrypted meaning that raw data is never exposed; and (3) Blockchain-Based Audit Logs: creates

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log entries for each access or update of a dataset in a tamper-proof manner that holds the organization accountable. These technologies support organizations in meeting privacy standards like the GDPR (EU) and HIPAA (U.S.) while making the data available for potentially useful services based on IPS data.

5.6.5. FL in IPS: opportunities and challenges

FL is often characterized as a privacy-preserving ML method because the data stays on edge devices (like a robot or mobile agent) and only model updates are sent to an edge server. This means that the raw location data never leaves the space in which it is locally based, providing more privacy to a user. There are, however, some technical reasons why FL is not simply translatable to IPS. (1) Non-IID Data: IPS devices deployed in different contexts (like hospitals and malls) will collect different data types. This data non-uniformity (the non-IID distribution between the data) can lead federated models to be slow to converge or less effective. (2) Communication Overhead: FL often entails regularly taking updates of the models between edge devices and the server, whereby strong communication and consistency in that communication must exist. In situations involving edge devices, such as robots that are continuously moving (such as in a warehouse), it may be impractical to ensure communication. (3) Device Limitations: IPS nodes are either embedded systems in the device itself or robots that do not have access to significant data processing or battery. This limited capability is exacerbated by running tasks/users of on-device training, limiting their subsequent abilities. (4) Privacy Is Not Guaranteed: Even though raw data is not privy to sharing, there are still types of model update-based attacks that make it possible to leak raw data from being able to utilize a type of model inversion or gradients (gradient leakage).

These challenges are not just theoretical; they have been observed in real-world pilot implementations:

- FL-PMI for Smart Healthcare [Arikumar et al.]: This system used FL with wearables to monitor patient movement. While highly accurate, it faced difficulties in training on unlabeled data and adjusting for varied body sensor placements [177].
- Drone-Based Hospital Perimeter Surveillance [Gokulakrishnan et al.]: FL helped preserve privacy during visual monitoring but introduced latency and required significant edge-side computation [178].
- Smart Wheelchair System for Pilgrims [Mohammed et al.]: FL supported distributed learning across wheelchairs with secure IoT connectivity. Despite improved real-time adaptability, data aggregation bottlenecks and privacy threats from model inversion were reported [179].

Together, these examples validate that FL offers promise for privacy in IPS but is not a plug-and-play solution. Its effectiveness depends on how well it is tailored to the deployment environment's computational limitations, connectivity constraints, and data characteristics. As such, hybrid approaches combining FL with secure aggregation, differential privacy, and blockchain-based audit trails may offer more viable, robust privacy protection for IPS systems in real-world deployments [180, 181].

5.6.6. Ethical outlook

Privacy in IPS cannot be a box ticked; it must be a fundamental underpinning for ethical acceptance and trust. Regardless of whether it is an AI delivery robot in a hospital or a retail tracking system using UWB, transparency, control, and data minimization should be guiding factors. FL is still in its infancy, and while it holds promise, it will face challenges in the IPS context that will require further research. The IPS community can work towards innovative, fair, secure, and respectful systems by integrating technological safeguards with human-centered consent mechanisms and continuous ethical audits. Ultimately,

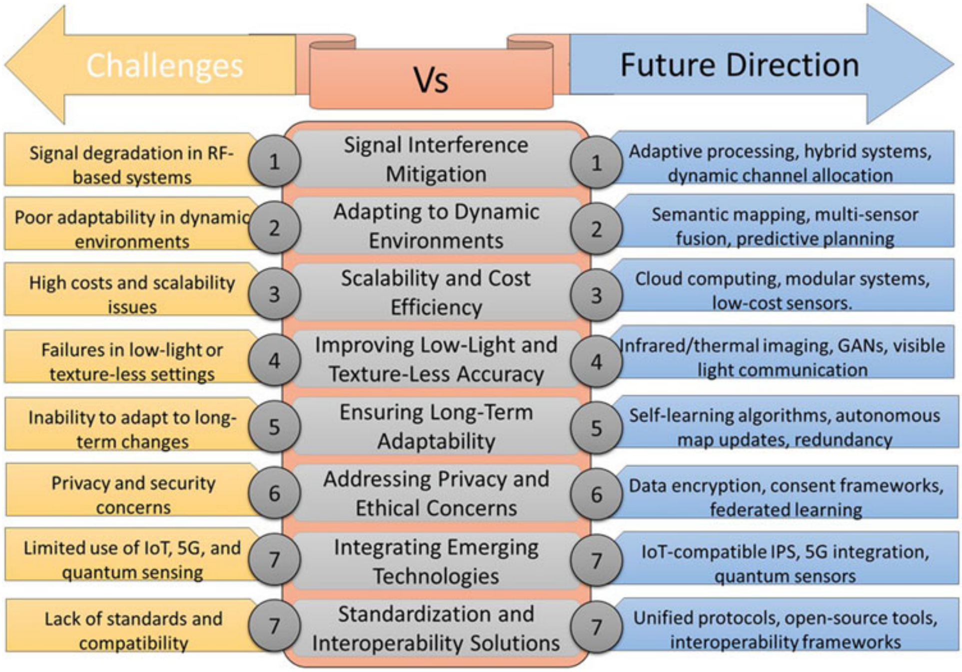

Figure 8. *Challages and future direction.*

ethical design in IPS is not just about compliance with laws and regulations; it is about respecting the individual in all the choices made by the system [182, 183].

5.7. Integration with emerging technologies

Limited exploration exists regarding integrating IPS with emerging technologies such as the Internet of Things, 5G networks, and quantum sensing. This gap restricts IPS from achieving its full potential in modern applications. IoT-compatible IPS solutions can leverage IoT devices for enhanced localization and context-aware navigation. 5G networks' high bandwidth and low latency can be exploited to improve real-time positioning accuracy. Quantum sensors offer the potential for achieving unprecedented accuracy and reliability in indoor positioning [184, 185].

5.8. Standardization and interoperability

The lack of standardized protocols and interoperability across different IPS technologies limits widespread adoption and integration. This fragmentation results in inefficiencies and compatibility issues in multi-system environments. Unified protocols developed through industry-wide collaboration can ensure compatibility between different IPS technologies. Open-source tools and frameworks can accelerate innovation and adoption. Interoperability frameworks that integrate multiple IPS technologies can enable seamless operations across diverse platforms [186].

Addressing the outlined research gaps requires a multidisciplinary approach combining sensor technology advancements, artificial intelligence, and system integration. By overcoming these challenges, future IPS can achieve higher accuracy, robustness, and scalability, unlocking their full potential across diverse applications such as industrial automation, healthcare, and public safety. The proposed solutions address current limitations and pave the way for innovative applications, ensuring that IPS remains a cornerstone technology in the era of autonomous mobile robotics (as shown in Figure 8).

6. Conclusion

Based on the detailed exploration of IPS in mobile robotics, this manuscript highlights the field's transformative advancements, challenges, and future potential. IPS technologies such as LiDAR, Visual SLAM, ultra-wideband, and hybrid systems enable robots to navigate complex indoor environments precisely. Despite advancements, issues like cost, signal interference, and dynamic environmental conditions persist. The manuscript emphasizes the role of interdisciplinary innovation, integrating artificial intelligence and the Internet of Things, to overcome these barriers. Practical applications span healthcare, industrial automation, and public safety, showcasing IPS as a cornerstone for advancing robotic autonomy. By addressing current gaps and prioritizing privacy and ethical considerations, this study provides a roadmap for researchers and industry stakeholders to foster innovation and redefine the capabilities of indoor localization systems.

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