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REVIEW ARTICLE

Indoor positioning system for warehouse environment: A scoping review

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ABSTRACT - Advanced technologies and automation, driven by Indoor Positioning Systems (IPS), transform businesses by enhancing efficiency, intelligence, and digitalization. Despite the critical role of IPS, there remains a lack of comprehensive reviews focusing specifically on their applications in warehouse inventory management. To bridge this gap and provide actionable insights for both research and practical implementation, this study conducts a systematic literature review following the PRISMA checklist. Centered around three key research questions, this review explores the scope of IPS applications in warehouse environments, the specific technologies employed, and the methods to evaluate IPS performance. This paper analyzes the fundamental principles and recent applications of widely adopted indoor positioning technologies, including Wi-Fi, UWB, RFID, VLC, IMU, Computer Vision, and LiDAR. Furthermore, this paper evaluates IPS technologies through five key evaluation criteria, highlighting their advantages, limitations, and challenges. This study provides a comprehensive understanding of IPS technologies in warehouse inventory management, offering actionable methods to evaluate their performance. The insights presented aim to deliver strong decision support for researchers and practitioners seeking to optimize inventory operations in warehouse environments.

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1. INTRODUCTION

In recent years, indoor mobile robots have increasingly changed our lives thanks to the rapid development of robotics and sensor technologies. Boston Dynamics' Spot and Atlas robots are already proficient at assisting humans with complex tasks in everyday scenarios [1]. Additionally, an increasing number of robotic products are being used in the fields of industrial automation [2], warehousing and logistics [3], surveying and mapping [4], medical care [5], disaster response, and home services [6] to replace humans in performing repetitive and laborious tasks and to reduce human errors. As robotic technology continues to evolve, a greater diversity of fields can be expected to benefit from this technology in the future. Due to indoor environments' intricate and dynamic properties, Indoor Positioning Systems (IPS) have emerged as a significant gap in the advancement of location-based technologies. Unlike most outdoor positioning systems, which rely on the Global Navigation Satellite System (GNSS), IPS has challenges because GNSS signals are severely attenuated in indoor environments [7]. This attenuation can significantly reduce the accuracy of positioning technologies, such as satellite-based navigation systems, when used indoors, posing considerable challenges to developing effective indoor positioning systems [8]. Therefore, the research of IPS is attracting significant attention.

IPS has garnered considerable attention and is useful in various indoor scenarios because most indoor mobile equipment operations rely on accurate positioning information. IPS can provide precise positioning information within indoor environments by utilizing a variety of sensors, wireless communications, and advanced positioning algorithms [9]. Sensors such as Wi-Fi, Bluetooth, Radio Frequency Identification Device (RFID), Ultra-Wideband (UWB), ultrasound, infrared, vision sensors, Light Detection and Ranging (LiDAR), and inertial measurement units (IMU) are leveraged by these systems to capture and analyze data related to signal strength, time delays, distances, directions, and angles. These systems offer positioning and tracking information in indoor environments, facilitating various applications, including indoor navigation. With the development of smart warehouses, mobile intelligent equipment is beginning to assist humans in warehouse operations such as inventory review, internal logistics, cycle counting, and stocktaking [9]. IPS plays a pivotal role in the advancement of modern smart warehouses. The basic characteristics of smart warehouses can be classified into the following categories: information interconnection, equipment automation, process integration, and environmental sustainability [10]. IPS is beneficial in all these aspects, especially for mobile equipment in warehouses represented by autonomous mobile robots [11]. For example, when IPS is applied to smart forklifts or Automated Guided Vehicles (AGVs) in a smart warehouse system [12], it allows these devices to run smoothly, and their movements are not restricted by changes in logistics activities or shelf layouts [13]. This technology also ensures real-time goods counting in dynamically changing warehouse environments, enabling faster goods picking, increased accuracy in warehouse operations, reduced operational costs, and minimized manual errors [14]. Combining robots, drones, and self-driving cars

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can achieve partial or complete autonomy for most warehouse operations tasks [15]. These systems are instrumental in improving operational efficiency across various domains, including inventory management, logistics, and warehouse digitization. Among these applications, inventory management is a crucial component of warehouse operations, directly influencing stock reliability, economic performance, and productivity.

However, to the author's best knowledge, no relevant scoping reviews have been conducted regarding IPS applications to warehouses. The main contributions of this review are:

i) Describing current applications of IPS in warehouse environments.
ii) Offering a comprehensive review of the current technology path for IPS applied in inventory-related tasks.
iii) Proposing a framework for evaluating different IPS technologies applied in inventory management.
iv) Providing guidance and prospects for future research on IPS technologies in inventory management, highlighting unresolved challenges and potential innovations.

The article is structured as follows: Section 1 outlines the background of IPS applications in warehouse environments, explains the significance and necessity of focusing on inventory management, and clarifies the objectives of this scoping review. Section 2 presents the research methodology used for this scoping review. Section 3 presents relevant results related to the research objectives, focusing on inventory management applications. Section 4 discusses the findings, proposes practical recommendations, and concludes the review.

2. SCOPING REVIEW METHODOLOGY

The methodology of this research adheres to the scoping methodological framework proposed by Arksey and Hilary [16] and the Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) execution standards set forth by Tricco and O'Malley [17]. Additionally, techniques from other review research methods, such as systematic review and meta-analyses, are referenced [18]. The ScR research method allows for a comprehensive and objective review of research in a specific field. Utilizing the standardized Scoping Reviews (PRISMA-ScR) Checklist enhances the efficiency of the review process, making the results valuable to readers, policymakers, and practitioners.

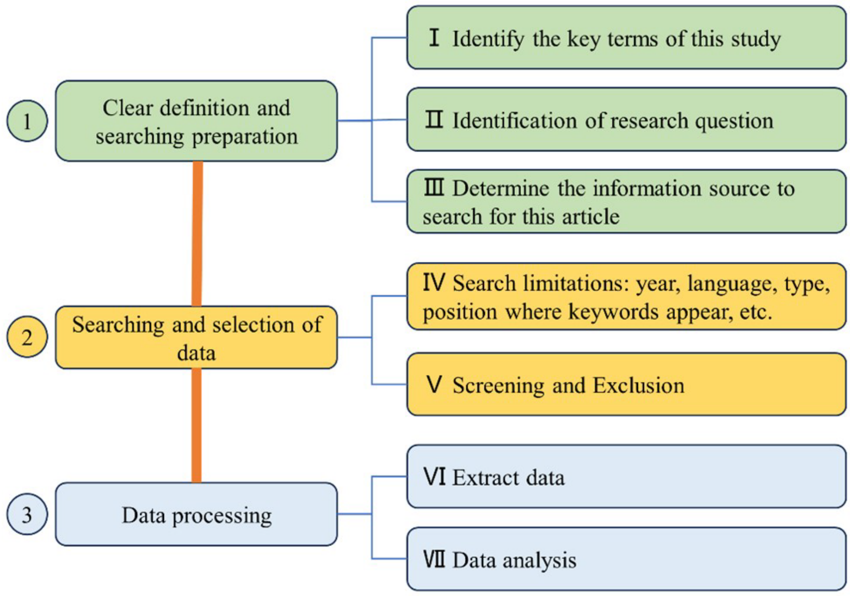


Figure 1. Scoping review process [16]

The PRISMA-ScR Checklist [17] and other review studies that employed this method [20-22] were synthesised. The research methodology primarily encompasses stages such as "Clear Definition and Searching Preparation," "Searching and Selection of Data," and "Data Processing," which can be further subdivided into seven detailed steps. The process of the scoping review undertaken in this paper is depicted in Figure 1.

2.1 STAGE 1: Definition and Searching Preparation

2.1.1 The key terms identification

The criteria of the PRISMA-ScR execution standard [12] are followed in this section for a pre-search investigation preparation process. Initially, the focus is on identifying key terms and providing accurate conceptual explanations for subsequent searches. However, it was found that the descriptions or concepts of these terms often lack consistency. Key concepts, similar terms, and near-synonyms related to the main research questions RQ1, RQ2, and RQ3 are synthesized and presented in Table 1, accompanied by brief explanations.

Table 1. Key terms

Key terms	Abbreviation & Synonyms	Related terms	Explanation
Warehouse	None	Cargo, Inventory, Shelf, Stock,	A warehouse is a large facility for storing goods, including storage space, inventory management, and loading areas.
Indoor Positioning	IPS indoor location, indoor navigation, Odometry	Sensors, Signal Sources, Mapping and Localization,	Indoor positioning refers to the technology or methods used to track the location of objects or individuals within indoor environments.
Mobile Robot	Mobile Robotic,	UAV (Unmanned Aerial Vehicle), MAV (Micro Aerial Vehicle) AGV, Drone,	In a warehouse setting, mobile robots, often called logistics or storage robots, are automated devices that handle inventory and logistics tasks.
Algorithm, Technology	Techniques, Method	Application	The technology or algorithm mentioned here pertains to the key technologies used in the IPS for mobile robots in a warehouse setting.

The initial search was conducted to refine the scoping review protocol, enhance the research questions, and adjust the search terms, upon which a more precise formal search would be conducted. The key terms employed in the search are defined in Table 1, and their synonymous expressions are elaborated.

2.1.2 Identification of research question

A comprehensive scoping review [17] addressing the questions outlined in Table 2 is aimed to be provided by this study. Through this approach, an in-depth exploration of historical development, a thorough comparison of diverse IPS technologies suitable for indoor warehouse environments, and the identification of research trends specifically applicable to inventory management within warehouse settings are offered to the reader.

Table 2. Ultimate tensile strength values and elongation to fracture

No.	Research Questions	Goal
RQ1	What are the current IPS applications in a warehouse environment?	Explore the applications of IPS in a warehouse environment, specifically focusing on identifying the role and criticality of IPS implementation in inventory management.
RQ2	What current IPS technologies are utilised explicitly for inventory management in warehouse environments?	Identify the techniques applied to IPS in a warehouse environment for inventory management, focusing on the key methods used for implementation and evaluating the advantages and limitations of each technology in enhancing inventory tracking and control.
RQ3	How to evaluate different IPS inventories for logistics management applications in a warehouse environment?	Develop a comprehensive evaluation framework for comparing IPS technologies in warehouse environments, focusing on their effectiveness, efficiency, and suitability for inventory management.

2.1.3 Determine the information source

Based on the findings presented in Table 3, it can be concluded that the relevant search terms for the scope of this scoping review include warehouse, indoor positioning, robot, navigation, and other related terms. Web of Science (WOS), Scopus, and Institute of Electrical and Electronics Engineers (IEEE) were selected as the search databases because nearly all peer-reviewed literature in the field of engineering technology application can be searched through the combination of these three databases.

2.2 STAGE 2: Data Searching and Selection

The flow chart of article inclusion and exclusion, based on the PRISMA execution standard [18], is displayed in Figure 2. The steps for search preparation, sorting of search results, screening abstracts and conclusions, and full-text screening are included. Steps IV and V will be utilized to detail how articles for inclusion in the review scope were obtained.

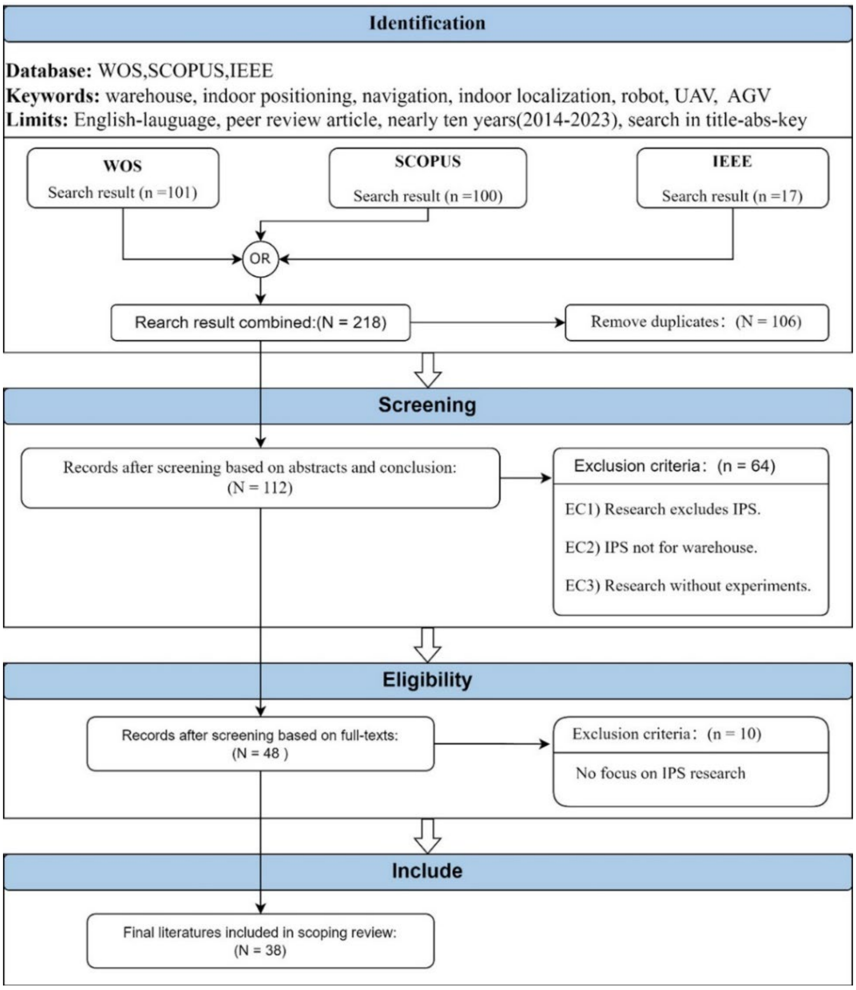


Figure 2. Flow chart of article inclusion and exclusion based on PRISMA criteria [18]

2.2.1 Searching limitations and keywords

The search strategy was designed to ensure comprehensive coverage of relevant literature on IPS technologies in warehouse environments. Searches were conducted in three major academic databases, Web of Science (WOS), IEEE Xplore, and Scopus, selected for their extensive engineering and technology-related publications indexing. The search queries combined keywords related to indoor positioning systems (e.g., "Indoor Positioning System," "IPS," "indoor localization") with terms specific to warehouse applications (e.g., "warehouse," "inventory management," "logistics"). Boolean operators such as "AND," "OR," and "NOT" were employed to refine the search scope, as illustrated in Table 3.

Table 3. Searching keywords and limitations

Database	Search terms
Scopus	(TITLE-ABS-KEY (warehouse) AND TITLE-ABS-KEY ("robot*" OR "drone" OR "UAV" OR "AGV" OR "MAV") AND TITLE-ABS-KEY ("indoor positioning" OR "indoor localization" OR "navigation")) AND PUBYEAR > 2013 AND PUBYEAR < 2024 AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "re")) AND (LIMIT-TO (SUBJAREA , "ENGI") OR LIMIT-TO (SUBJAREA , "COMP"))
WOS	(TS=(warehouse)) AND (TS=(indoor positioning) OR TS=(indoor localization) OR TS=(navigation)) AND (TS=(robot*) OR TS =(drone) OR TS =(UAV) OR TS =(AGV) OR TS =(MAV)) Refined By: Publication Years: 2014 2015 or 2023 or 2022 or 2021 or 2020 or 2019 or 2018 or 2017 or 2016 or 2015 or 2014, Document Types: Article
IEEE	("Abstract": warehouse) AND ("Full Text & Metadata":"robot*" OR "Full Text & Metadata":"drone" OR "Full Text & Metadata":"AGV" OR "Full Text & Metadata":"MAV" OR "Full Text & Metadata":"UAV") AND ("Abstract":"indoor positioning" OR "Abstract":"indoor localization" OR "Abstract":"navigation") Filters Applied: Journals2014 - 2023

Specific filtering criteria were applied during the search to improve relevance and reliability. These criteria included: Articles published in English, Peer-reviewed journal articles and conference papers, Publications from the past decade (2014–2023); and a search scope limited to the title, abstract, and keyword sections. An initial search was conducted in June 2023 using these criteria, resulting in 100 articles from Scopus, 101 articles from WOS, and 17 from IEEE. After merging the results from all three databases and eliminating duplicates, 112 articles were retained for further filtering. The search process followed the PRISMA flowchart depicted in Figure 1. As the initial search results were reviewed, the search strategy was iteratively refined by adjusting keywords and Boolean operators to ensure comprehensive coverage. This iterative refinement maximized the inclusion of relevant studies while maintaining a focus on IPS technologies applied to warehouse environments.

2.2.2 Screening and exclusion

The inclusion and exclusion criteria were applied to ensure the selected articles aligned with the study's objectives. The exclusion criteria are presented in Table 4, emphasizing the selection of studies directly relevant to IPS applications in inventory management within warehouse environments. Articles were included if they Discussed IPS technologies specifically in the context of warehouse environments. Focused on inventory management, logistics, or warehouse digitization tasks. Provided experimental data, theoretical analysis, or practical case studies relevant to IPS applications. Articles were excluded if they focused solely on outdoor positioning systems or technologies unrelated to warehouse operations. Lacked detailed descriptions of IPS implementation or applications and were review papers or non-peer-reviewed publications. The screening process was conducted in two stages: titles and abstracts were reviewed to eliminate irrelevant articles, followed by a full-text review to ensure alignment with the inclusion criteria. In this phase, the 112 selected articles were reviewed thoroughly. Focus was placed on their titles, abstracts, and keywords to ascertain alignment with the research topic. After the abstracts and conclusions were screened, 64 articles were excluded for not matching the subject of this study based on conditions EC1, EC2, and EC3. A comprehensive review of the remaining 48 full-text articles was then conducted. It was identified that 10 of these articles neither primarily focused on IPS nor provided detailed information about the implementation process of IPS. As a result, these 10 articles were excluded from further analysis. The methodology employed to extract and analyze data from the remaining 38 selected articles will be elaborated upon in the subsequent sections.

Table 4. Exclusion criteria

No.	Exclusion criteria	Description
EC1	Exclusion of research that does not involve IPS	Literature not primarily focused on IPS is excluded, as it is deemed irrelevant to the study
EC2	Exclusion of items not relevant to inventory management in a warehouse environment	Literature in which IPS is not applied, or is not intended to be applied, in the warehouse environment is excluded
EC3	Exclusion the literature that without real experiments, the IPS	Literature that has not been tested in practice or whose simulation tests do not resemble real-world warehouse environments is excluded

2.3 STAGE 3: Data Processing

2.3.1 Data Extraction

The literature information included in the scoping review was categorized into three types: foundational data, distinctive data, and experimental data. This categorization facilitated the organization and comprehensive analysis of the extracted information. Foundational data included the title, author, publication year, keywords, and journal. A clear timeline of technological development in this field was outlined through the analysis of foundational data. Development trends were further analyzed by incorporating distinctive data. Distinctive data comprised research (application) objectives, conclusions, and future work. A clear understanding of the research problem's focal points, urgent issues requiring attention, and current challenges was gained through the organization and collection of distinctive data from each article. Experimental data included technologies used in the study, experimental (testing) platforms, experimental (testing) environments, accuracy, cost, energy efficiency, and scalability. A comprehensive analysis of the strengths and weaknesses of various techniques, methods, and algorithms was conducted by organising detailed experimental data and formulating a comprehensive evaluation framework. A standardized form developed in Microsoft Excel was employed to uniformly record data from articles that had passed the initial filtering and selection steps to ensure a systematic data extraction process.

2.3.2 Data Analysis

Quantitative and qualitative analysis was applied to the data and information extracted from the selected articles. This step involved the organization and analysis of data for RQ1, RQ2, and RQ3. To comprehensively address RQ1, the basic information of the included articles was first compiled. Based on the objectives of each study, the direction of IPS applications in warehouse environments over the past decade and the proportion of relevant literature were analyzed. For RQ2, both foundational and experimental data were utilized to generate a timeline that captures the development of indoor positioning technologies in warehouse environments within the scope of the review. Regarding RQ3, key elements of experiments were derived from the Experimental data in the reviewed articles. An evaluation framework explicitly tailored for indoor positioning technologies in warehouse environments was established by referencing the house of quality evaluation system. Figure 3 outlines the review protocol employed in this study, which provides a systematic methodology for capturing knowledge and insights related to the topic and all relevant variables in a structured manner. The results of the scoping review based on the proposed review protocol are presented in the subsequent section.

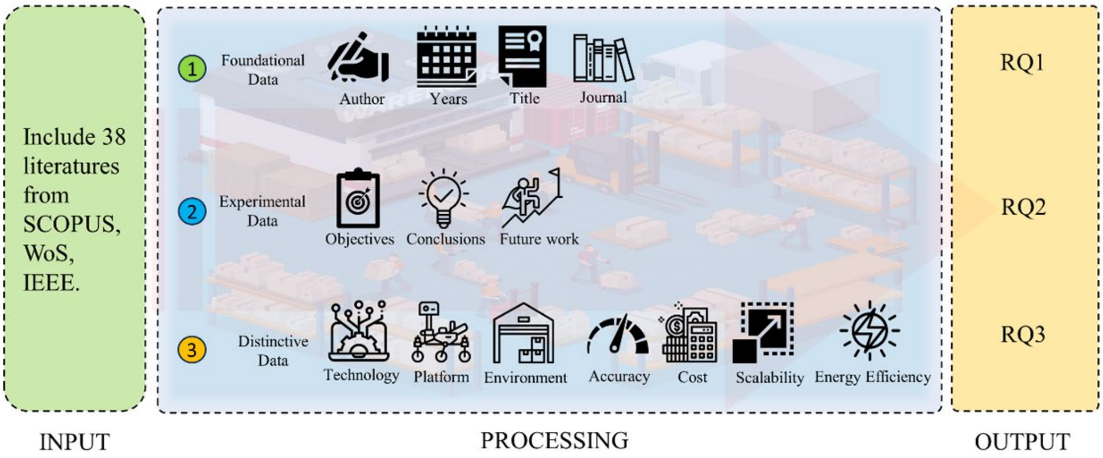


Figure 3. Conceptual framework and review protocol

3. DATA ANALYSIS AND DISCUSSION

In this Section, an analysis of the relevant data from the literature within the review scope was conducted. Statistical methods, connected papers [22] (a graphical literature search tool that utilizes co-citation and bibliographic coupling concepts to compile relevant literature lists and graphics), data visualization, and other means were employed to provide descriptive presentations and analysis of the results. The primary focus of this chapter was on describing the characteristics of the literature and presenting data relevant to the research questions (RQs).

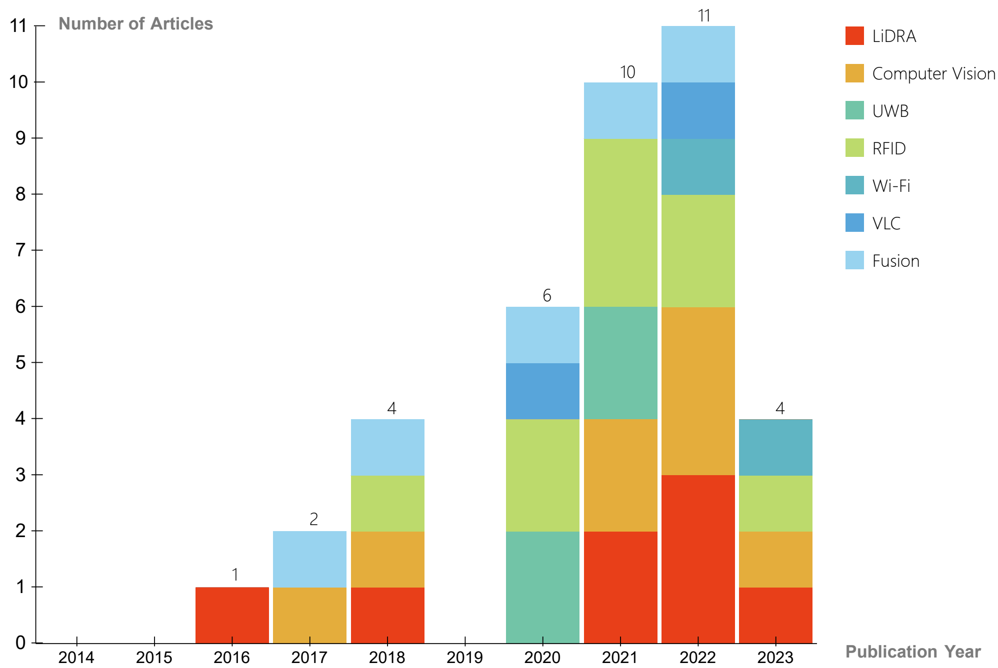


Figure 4. Publication counts of included articles in the past decade (2014-2023)

3.1 Literature Characteristics

An analysis of literature features can assist researchers in gaining a comprehensive understanding of the status and development trends in the research field. Initially, the quantity and temporal distribution of the included literature were analyzed to comprehend the research activity and trends in the application of IPS in warehouse environments. The 38 articles included in this study were published between 2014 and 2023. As observed in Figure 4, the number of publications has been increasing annually, with significant acceleration noted in recent years. More than half of the articles were published in the last three years, reaffirming the timeliness and appropriateness of conducting a comprehensive review in this field. It is worth noting that no articles were identified for the year 2019. This absence results from applying the exclusion criteria, where studies not directly relevant to the research objectives, particularly those lacking practical implications for IPS applications in warehouse environments, were excluded. Next, the keywords and topics of articles within the research scope were analyzed to identify main research directions, hot topics, and focal points, thus revealing research themes and trends. Interrelationships among these elements were examined, and a co-occurrence network was presented in Figure 5.

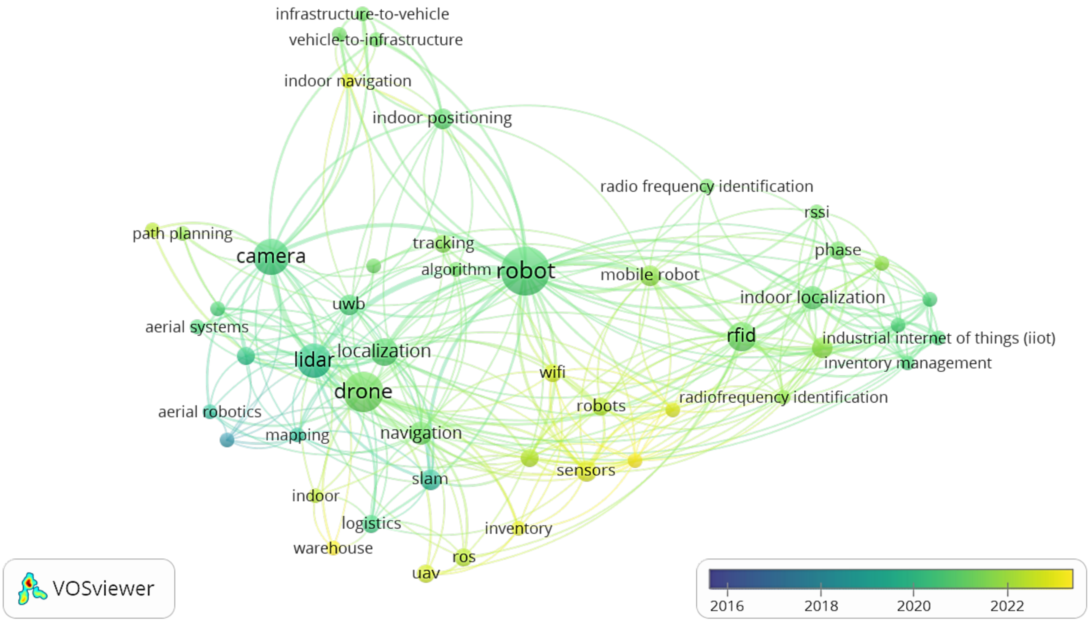


Figure 5. Keywords co-occurrence network based on the selected 38 articles

In Figure 5, each node expresses a keyword, representing a topic in the field of IPS research in warehouse environments. The node size indicates the number of articles related to the topic. Nodes are linked by arcs, signifying the co-occurrence between two topics, and the thickness of these arcs represents the closeness of the subjects. The legend in the lower right corner of the figure explains that the color of different nodes corresponds to the year of publication of their related literature, revealing the development trend of popular topics in the field. It is observed from the network that the primary research objects in this theme are robots (including UAVs), and the main positioning technologies of interest comprise LiDAR, Computer Vision, RFID, and UWB. A significant increase in warehouse research in recent years is also noted. In summary, an analysis of the literature has revealed the emerging popularity of the field, but it has not provided meaningful insights into the application of IPS in warehouse environments. To conduct a comprehensive investigation, an in-depth analysis and discussion will be centered around the research questions based on the literature within the scope of this review.

3.2 RQ1: What are the current IPS applications in the warehouse environment?

In the 38 articles included within the scope of this review, applications of IPS in warehouse environments are explicitly mentioned in 30 articles. In comparison, the remaining 8 articles focus solely on contributions to algorithms without testing in warehouse application scenarios. Analysis of the survey results reveals that the most frequent area of research is warehouse inventory applications; 14 out of the 30 articles (46.67%) focus specifically on this area. Since inventory management is critical to production efficiency and overall economic performance, a significant portion of IPS research in warehouse environments is allocated to improving these processes. Similarly, warehousing logistics management is another primary area where IPS is applied, as indicated by 13 articles (43.33%). For the maintenance of efficient warehouse operations, a well-functioning warehousing logistics management system is deemed essential. Research in this domain primarily concerns the localization or navigation of mobile devices like AGVs or forklifts within the warehouse setting. Furthermore, the application of IPS in the digitization of warehouses was discussed in 3 articles (10%). Two of these articles concentrate on constructing 3D models of warehouses, while the third article focuses on stack measurement for storing bulk materials. A summary of IPS applications in warehouse environments and corresponding literature is provided in Table 5. While reviewing applications of IPS in warehouse environments, the contributions and future works mentioned in the articles under review were also investigated. It was observed that challenges identified in prior research were targeted for resolution in all scoped articles or enhancements in one or more performance metrics were aimed for. These articles focus on metrics such as efficiency, safety, accuracy (precision), robustness (stability), and cost. Figure 6 illustrates the distribution of these research articles over the years and their corresponding performance metrics. The horizontal axis represents the years of publication, while the vertical axis delineates the metrics. Each performance metric is depicted by a bar graph, where the intensity of the color signifies the relative number of articles published in that specific period. Darker shades indicate fewer articles, while lighter shades suggest more articles.

Table 5. Applications for IPS in the warehouse

Application areas in the warehouse	Percentage	Articles
Inventory	46.67%	[23],[24],[25],[26],[27],[28],[29],[30],[31],[32],[33],[34],[35],[36]
Logistics management	43.33%	[37],[38],[39],[40],[41],[42],[43],[44],[45],[46],[47],[48],[49]
Warehouse Digitization	10.00%	[50],[51],[52]

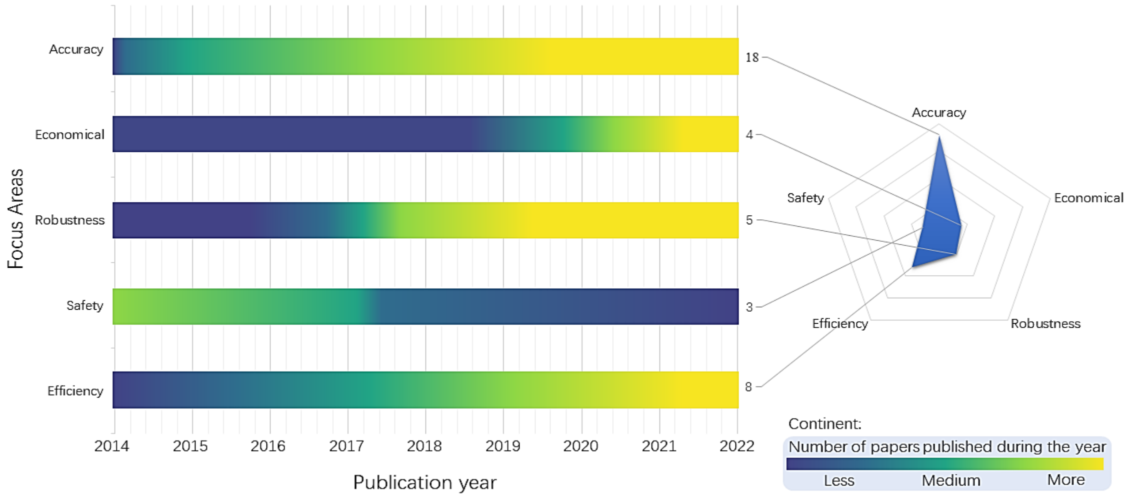


Figure 6. Areas of focus for IPS applications in warehouses (2014-2023)

From the graph, it was observed that some articles address multiple performance metrics simultaneously. A focus on the positioning accuracy of IPS is seen in a total of 18 articles. A significant increase in articles addressing accuracy-related issues in the past three years indicates a growing interest in this research area. Conversely, efficiency is the focus of 8 articles, with a steady growth rate observed year over year. Research on robustness, cost-effectiveness, and safety has received relatively less attention, although notable trends are still observable. An increase in research on system robustness since 2017 is evident, whereas hardly any relevant studies existed before that period. Starting in 2020, articles featuring research on cost-effectiveness and economics appeared. In contrast, a declining trend in publications addressing safety concerns after 2017 was noticed. Inventorying in a warehouse involves auditing goods, real-time tracking of inventory, and cross-checking inventory data with financial records to ensure accurate warehouse management. In traditional warehouse operations, this process relied heavily on manual staff or third-party audits to identify discrepancies in stock counting, inventory storage, and accounting. With the integration of IPS technologies, inventory management can be evolved into a highly automated and precise process, enabling real-time updates, reducing human errors, and enhancing overall efficiency. As illustrated in Figure 7, IPS technologies have been applied across three main warehouse tasks: inventory management, logistics management, and warehouse digitization. Among these, inventory management is the most frequently studied application, with the largest share of articles (46.67%) focusing on tasks such as real-time inventory tracking, cycle counting, and stocktaking. This dominance underscores the critical role of inventory management in warehouse operations, where precise localization and tracking are essential for operational efficiency.

Logistics management accounts for 43.33% of the studies, primarily focusing on moving and handling goods, such as internal transportation, warehousing, and order picking. However, many logistics management tasks, particularly those involving the receipt, storage, and dispatch of goods, are closely tied to inventory management. For example, registering incoming goods and preparing items for dispatch relies on accurate inventory data and real-time localization capabilities provided by IPS technologies. In comparison, warehouse digitization comprises only 10% of the articles, focusing on environmental monitoring and surveillance tasks. While these applications are critical for safety and operational monitoring, their direct impact on inventory management is less pronounced. From this analysis, it can be concluded that inventory management represents the largest and most impactful application of IPS technologies and forms the foundation for many logistics-related tasks. This finding highlights the importance of inventory management when evaluating and implementing IPS technologies in warehouse environments.

From Figure 7, it was noted that most research related to inventorying tasks utilizes UAVs. This preference is primarily attributed to the often elevated positions of shelves in warehouse environments, to which UAVs can easily fly, allowing them to perform real-time inventory checks and stocktaking tasks efficiently. UAVs exhibit distinct advantages in such scenarios compared to traditional ground-based mobile robots, particularly in high-density storage spaces and multi-level warehouses. Furthermore, UAVs enable the rapid scanning of inventory and the generation of accurate, up-to-date data critical for effective warehouse operations. Logistics management tasks within the warehouse, as shown in Figure 7, primarily involve the internal circulation of goods, including warehousing, material flow, transportation, and express delivery. In these tasks, mobile devices such as AGVs are predominantly utilized due to their ability to handle payloads and navigate efficiently within the warehouse. However, many logistics-related activities, such as receiving, storing, and dispatching goods, are inherently tied to inventory management processes. These activities rely heavily on accurate inventory data generated and maintained through IPS technologies, further highlighting the integral role of inventory management in warehouse operations. Lastly, tasks related to warehouse digitization focus on inspecting and surveillance personnel, equipment, environment, and goods within the warehouse to detect potential risks and ensure safety. While these tasks may seem distinct, the real-time data generated by IPS technologies for inventory tracking also contributes to monitoring warehouse conditions, demonstrating the interconnected nature of these applications. Mobile devices such as UAVs and AGVs, equipped with advanced IPS technologies, are instrumental across all these tasks, with inventory management forming the foundation for their broader applications.

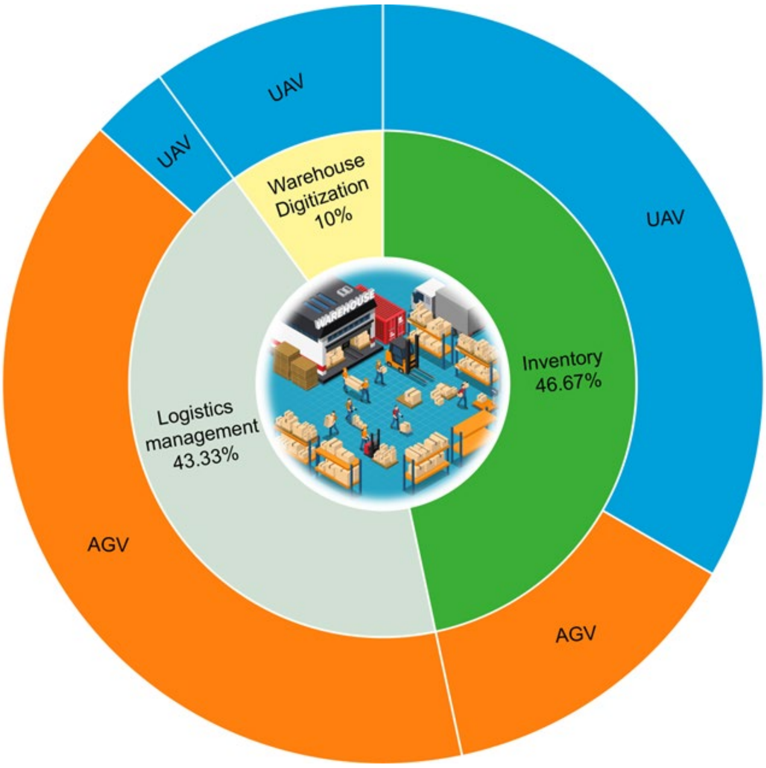


Figure 7. Application of IPS in a warehouse environment

In summary, various aspects of warehouse operations, including inventory, logistics management, and warehouse digitization, are covered by the current applications of IPS in warehouse environments. In inventory and warehouse digitization tasks, a significant performance has been shown by UAVs, which are widely used. In tasks related to logistics management, the predominant use of AGVs has been observed. Noteworthy is that the AGVs mentioned in the articles are equipped with indoor positioning capabilities and the ability to navigate indoors, differentiating them from traditional AGVs that follow predetermined routes. Therefore, a primary focus in the current applications of indoor positioning technologies in warehouses is the integration of IPS with mobile robots. Due to their superior space mobility, UAVs are mainly employed in inventory or inspection tasks. Conversely, logistics-related tasks necessitate mobile devices with specific payload capacities, resulting in a greater utilization of AGVs for these applications.

3.3 RQ2: What current IPS technologies are utilized explicitly for inventory management in warehouse environments?

The critical factor of technology choice for determining the suitability of an IPS for a given scenario is addressed in this section. A comprehensive review of indoor positioning technologies in warehouse environments was first developed. The technologies identified in the reviewed articles were initially classified, and the methods associated with different technology categories were subsequently organized and discussed in various research contexts. A deeper understanding of the relationship between IPS techniques and methods in the warehouse environment was gained by expanding a subset of the literature using the connected papers method. A comprehensive understanding of the current applications of IPS-related technologies in warehouse environments is aimed to be provided through these three steps in this chapter.

3.3.1 Classification of technology

In some existing reviews, summaries for IPS have been provided. However, most of these reviews focus on a general overview of IPS, with little emphasis on its specific application areas. This study initially examined existing categorizations of IPS technologies from past reviews. Table 6 compares categorization results from three representative reviews published within the last five years. Subsequently, a comprehensive overview of indoor positioning technologies applicable to warehouse environments was developed based on the articles included in our scoping review.

Table 6. Classification of IPS technology based on existing review papers (2017-2023)

Reviews	Technology(different)	Technology (similar)
Basiri et al. [53]	Infrared, Magnetometer	Wi-Fi (WLAN)
	Tactile Odometer	UWB
	Electromagnetic Systems	RFID
	Mobile Network	Zigbee
	Barometer	Bluetooth (BLE)
	Pseudo lite	Visible Light Communication (VLC)
Zafari et al. [54]	None	Acoustic (Ultrasound)
Mendoza-Silva et al. [55]	Tactile Odometer	Computer Vision (Camera)
	NFC	IMU

In their Meta-Review on IPS, Mendoza-Silva et al. [55] catalogued various mainstream indoor positioning technologies, including Light, Computer Vision, Sound, Magnetic Fields, Dead Reckoning, UWB, Wi-Fi, BLE, RFID, and ZigBee. It should be noted that technologies providing odometer information, such as inertial odometers and wheel encoders, were not included in their statistical analysis, as they were considered to achieve positioning indirectly. In contrast, in robot localization, these technologies were found to fundamentally serve the purpose of positioning [56]. Therefore, LiDAR technology was added, and some technologies (such as Bluetooth, Ultrasound, and ZigBee) that did not appear within the scope of our 38-article review were removed. An overview of the IPS technologies applicable to warehouse environments is provided in this section and summarized in Table 7. The technologies utilized in the articles scoped for our review are presented in this table, along with the accuracy reported in some representative studies. Although existing reviews contain literature that covers a broad spectrum of technologies, only those employed for IPS are considered in this study. For instance, in the paper by Krug et al. [23], although Computer Vision technology is mentioned, positioning information was achieved solely through LiDAR technology. Therefore, their positioning technology has been classified as LiDAR technology. The accuracy metrics presented in Table 7 were extracted from the articles within our review scope, and only the accuracy from representative research for each technology is displayed. The use of multi-sensor fusion techniques is also indicated with an asterisk (*) in the table.

As shown in Table 7. In recent years, Wi-Fi positioning technology has been widely applied in warehouse environments, providing innovative solutions to enhance warehouse automation efficiency. The WiSion system leverages Wi-Fi signal multipath effects and inertial sensors to estimate a six-degree-of-freedom state in complex indoor warehouse environments without requiring access point positions, adapting to obstacles and multipath interference [57]. KF-Loc combines machine learning and Kalman filtering, utilizing millimeter-wave equipment to achieve high-precision positioning in dynamic warehouse environments, significantly improving smart warehouse management efficiency [58]. The UWB localization method proposed by Zhao et al. [59] achieves centimeter-level accuracy for AGVs without predefined paths, significantly reducing warehouse automation costs while improving system robustness through data diagnosis and optimization algorithms. Monica [60] uses UWB technology to achieve high-precision localization for manual forklifts or personnel. It integrates with laser navigation, greatly enhancing the efficiency of positioning and managing various equipment and personnel in industrial warehouses. Li et al. [29] combined RFID technology with UAVs for warehouse inventory management, enabling efficient localization of tagged items on shelves and accurate horizontal and vertical classification. Alajami et al. [31] proposed the RFID-SOAN navigation system, which uses RFID tags as digital pheromones to help UAVs autonomously navigate and efficiently perform inventory tasks in mapless warehouses. Wu et al. [32] introduced the RF-SLAM method, which uses RFID devices to simultaneously localize robots and map tags, supporting rapid 3D spatial modeling in warehouse environments and enhancing warehouse automation capabilities.

Louro et al. [43] proposed a visible light communication technology applied to warehouse management, enabling bidirectional communication between infrastructure and autonomous robots and communication among robots. This system supports robot positioning, transmission of rack information, and interaction on the status of transported items, enhancing the efficiency of warehouse logistics management. Another application is a VLC-based indoor navigation system, which uses warehouse LED lighting infrastructure to provide positioning and navigation for AGVs. Through uplink and downlink communication, automated control of AGVs in warehouse environments is achieved, optimizing the logistics operations of modern warehouses. The Dual-LiDAR navigation system proposed by Zhang et al. [42]is applied in warehouses to enable precise autonomous transportation and logistics operations, meeting the demands of intelligent warehousing with efficient mapping and navigation. The Relative Preintegration (RP) method developed by Kim et al. [61] enhances the performance of multi-sensor fusion navigation systems, enabling fast and accurate IMU data processing and improving the adaptability and efficiency of robotic operations in dynamic warehouse environments. Kwon's [27] system enhanced UAV inventory inspections by ensuring safe navigation in narrow and poorly lit warehouse aisles, improving operational efficiency. Prakash et al. [49] showcased how leveraging structural features like racks and ceilings can support precise robot navigation, reducing errors and enhancing automation in large-scale warehouses. Beul et al. [24] developed an autonomous MAV system that navigates warehouse aisles, identifies stock on shelves, and avoids obstacles, enabling fully automated inventory inspections guided by a warehouse management system. Gago et al. [51] designed an aerial robotic system for smart inventory in stockpile warehouses, automating the measurement of bulk material volumes, such as fertilizers, with higher accuracy, safety, and efficiency, replacing traditional manual methods in challenging industrial environments.

Table 7. Summary of indoor positioning techniques in warehouses

Tech	Typical Accuracy	Remarks	References
Wi-Fi	Positioning accuracy with RMSE (root-mean-square error) is less than 37 cm [58]. Positioning and orientation errors are 31.77 cm and 2.27◦, within mild maximum errors and 95% confidence intervals [57]. Average errors of 89 cm are reported [28].	Despite a more significant error reported in the article [28], positioning across an expansive warehouse area is achieved.	[58], [28], [57]
UWB	An average error of approximately 20 cm and a maximum of around 40 cm are reported [38]. An average 42.08% reduction in localization error is noted in three different anchor setups compared to a baseline approach.	A significant reduction in error is achieved, but experiments in an actual warehouse are not conducted [59].	[38],[26], [59], [60]
RFID	Steady-state error averages no more than 28 cm [39]. Tracking accuracy ranges from 6 to 10 cm [29]. Position and orientation RMSE are 15 cm and 0.2 rad, respectively [63]*. A mean accuracy of 13 cm for 3D localization and 0.21 cm for 2D is noted [48]. The mean and standard deviation of robot localization via LiDAR SLAM is 11.9 cm and 5.4 cm [32].	RFID technology is identified as a mature tag information system extensively used in logistics and warehousing. Simultaneous localization of both goods and mobile robots is achieved using RFID technology [32].	[39],[27]*, [29],[63]*, [31],[48], [32], [47], [34]
IMU	An average accuracy of 4 cm is reported [42]*.	Both literature [61]* and [42]* discuss the utilization of IMU for improved positioning accuracy. However, IMUs are already integrated into many mobile robots, such as the Crazyflie nano-quadcopter mentioned in the literature [59], which does not address IMU sensor treatment. Hence, they are not included in this category.	[61]*, [42]*
VLC	Positioning delay is found to be less than 3ms [43].	The positioning approach in [43] is commonly employed to locate target areas, focusing on latency.	[40], [43]
Computer Vision	Average errors from ground truth are 3.8 cm for the proposed method [64]. After more than 60 m of flight, the final drift is less than 0.6 m, equating to around 1% [50]. Average and maximum localization errors are 3.12 cm and 25.68 cm, respectively [27]*. The average error in X and Y dimensions is less than 5 cm, and the angle is less than 0.1 radian [45]*.	Experimental results and engineering experiences are comprehensively shared in the paper [50]. Multi-sensor fusion for autonomous cargo inventory counting in real warehouses is accomplished in paper [27].	[23]*,[25]*,[30], [35],[37]*, [64]*,[50], [61]*,[49]*, [44],[45]*,[33]
LiDAR	An average positioning error of 11 mm and a maximum error of 26.18 mm are reported [41]. An average accuracy of 4 cm is noted [42]*. The mean distance error is 98.2 mm [46].	A comprehensive system, including laser-based positioning, planned navigation, obstacle avoidance, and information acquisition, is presented in the paper [24]. The Omniverse Isaac Sim simulation environment is employed in the paper [46], enhancing simulation experiment efficiency compared to traditional software like Gazebo.	[23]*,[24], [64]*,[61]*, [25]*,[52], [41],[51], [42]*,[65], [45]*, [46]

* Note: An asterisk (*) indicates using multi-sensor fusion techniques.

Building upon these advancements, integrating diverse technologies like Wi-Fi, UWB, RFID, VLC, and LiDAR demonstrates the growing potential for intelligent warehouse systems. These innovations not only improve the efficiency of logistics operations but also set a foundation for scalable, fully automated warehouse solutions. By addressing challenges such as navigation in GPS-denied environments, precise inventory management, and real-time communication between devices, these systems pave the way for smarter, safer, and more adaptable warehouses, meeting the demands of modern supply chain and logistics industries.

3.3.2 Relationship between technologies, techniques, and algorithms

While classifying the technologies, it was observed that specific techniques or methods corresponded to different technologies. To delve deeper into the underlying patterns and trends in IPS technology development, the methods employed to implement each technique were initially categorized based on the articles within the scope of this review. The relationship between Technologies, Techniques, and Methods is represented in a Sankey diagram, as displayed in Figure 8. In this diagram, three columns are presented, representing Technologies, Techniques, and Methods, respectively. Connections between these columns indicate various technical routes. The data visualized in Figure 8 is derived from the original data summarized in Table 7 of this paper. "Technologies" refers to the different types of technology utilized in IPS, "Techniques" specifies the unique ways a particular technology is deployed (such as specific signal attributes or types), and "Methods" predominantly alludes to the algorithms proposed in the research. Additionally, the label "Sensor Fusion" was added to account for studies that employed sensor fusion techniques for IPS implementation. Specific algorithm names did not explicitly characterize some optimization methods; these were marked as "Techniques-based" in their respective studies.

From Figure 8, popular technologies, including LiDAR, Computer Vision, and RFID, were discernible over the past decade. Preferred techniques, such as Time-of-Flight (TOF), Received Signal Strength Indication (RSSI or RSS), and Feature Matching, were also identified. In articles within the scope of this review that utilized LiDAR, focus was mainly placed on the implementation or optimization of IPS. These articles used point cloud data provided by LiDAR for positioning but omitted details on how LiDAR generated this point cloud data. After this observation, a search was conducted on LiDAR-related literature. It was found that TOF-based LiDAR is a widely employed technique for distance measurement in single-point depth sensing and 3D mapping [68]. Therefore, most research on LiDAR technology in this context utilizes TOF-based distance sensing, with variations in the algorithms employed for data processing. This Sankey diagram systematically illustrates the relationships between Technologies, Techniques, and Methods, clearly visualising how different technical pathways are applied in IPS research. The diagram is divided into three columns: the left column, Technologies, includes various types of technologies such as IMU, VLC, Wi-Fi, UWB, RFID, Computer Vision, and LIDAR. The middle column, Techniques, represents the specific application methods of these technologies, such as Signal-to-Noise Ratio (SNR), Angle of Arrival (AOA), Received Signal Strength (RSS), Time Difference of Arrival (TDOA), Visual Odometry (VO), and feature extraction. The right column, Methods, summarizes the algorithms and solutions proposed in related studies, including machine learning approaches, optimization methods, and fusion strategies.

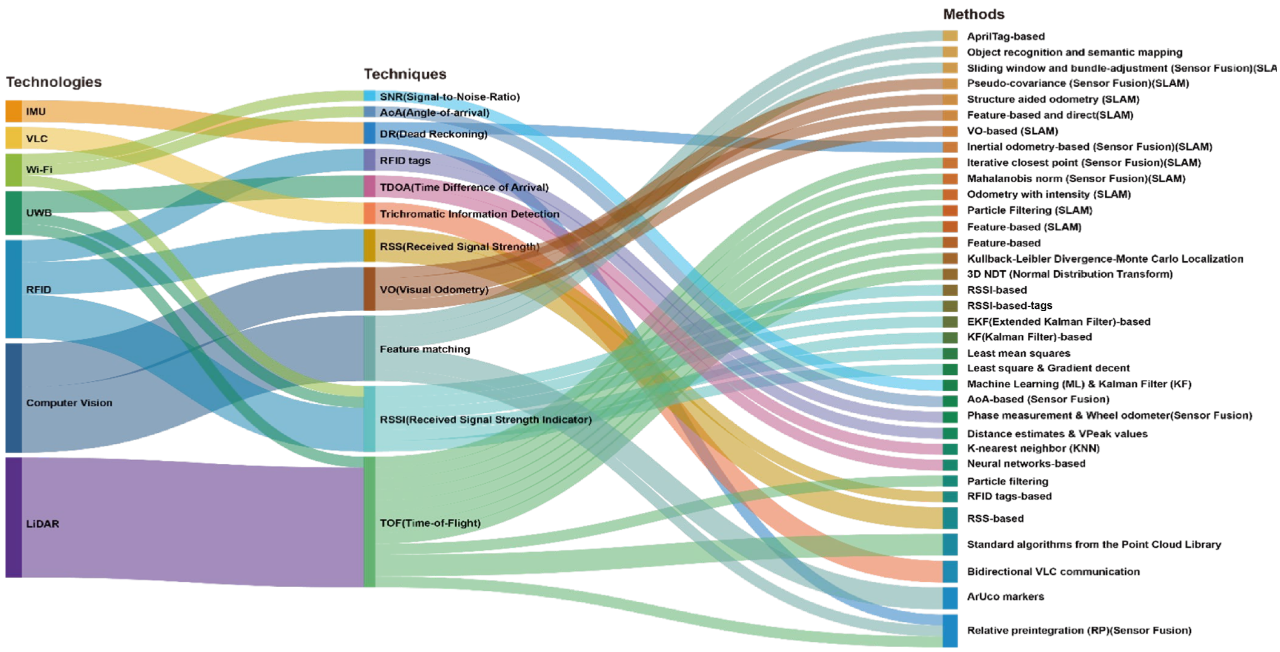


Figure 8. Relationship between technologies, techniques, and methods of IPS in warehouse environments

The connections between the columns illustrate the pathways from Technologies to Techniques and finally to Methods, showing how various technologies are applied to specific algorithms through techniques. For example, Wi-Fi technology is primarily associated with RSS and SNR techniques, which connect to multiple positioning algorithms. UWB technology is often linked with TDOA and trilateration methods, contributing to path planning and fusion strategies. Sensor Fusion is specifically highlighted, reflecting its cross-technology and multi-method applications. While not explicitly labeled with algorithm names, some optimisation approaches are summarized as “Techniques-based” pathways. It is important to note that the Methods listed on the right side of the diagram are derived from the original data summarized in Table 7 of this paper. By visualizing the data from Table 7, this Sankey diagram provides a comprehensive overview of the interconnections between technologies, techniques, and algorithms in existing research. It delivers a clear analytical framework for understanding these relationships and serves as a valuable reference for future research in selecting technologies and planning technical pathways.

3.3.3 IPS technology development in warehouse environment

In the previous section, the organization of technologies, techniques, and methods relevant to IPS was carried out within the scope of the review, and their relationships were identified. Despite the review being limited to 38 articles, various technologies were observed. Consequently, challenges were faced in providing a comprehensive and clear background for these technologies, techniques, and methods based solely on the articles within the review. A methodology involving the search for secondary and tertiary literature referenced in the primary articles was employed to address this issue. This approach enhanced the technology framework and gave readers a more comprehensive and detailed field review. The 38 primary articles included in the review and the classification results from Table 8 were input as original data into the connected papers system [22], and secondary and tertiary literature related to each technology was systematically identified. Literature that cited each technology extensively was meticulously examined, and an expanded review library of relevant literature was subsequently assembled. The literature thus discovered is presented in Table 8.

Table 8. Ultimate tensile strength values and elongation to fracture

Tech	Tracking Literature
Wi-Fi	[66], [67], [68], [69], [70], [71], [72], [73], [74], [75], [58], [76]
UWB	[77], [78], [79], [80], [81], [82], [83], [84], [85], [86], [87]
RFID	[88], [89], [90], [91], [92], [93], [94], [95],
VLC	[96], [97], [40], [43]
IMU	[98], [99], [100], [101], [61]
Computer Vision	[102], [103], [104], [105], [106], [107], [108], [109], [110], [111], [112], [113], [114]
LiDAR	[115], [116], [117], [118], [119], [120], [121]

Seven different types of IPS-related technologies were included in the review. These technologies were classified into two types based on the measurement medium: wireless signals, such as Wi-Fi, UWB, and RFID, and other physical signals, like Computer Vision, LiDAR, IMU, and VLC. Algorithms for indoor positioning technologies based on radio signals were categorized into AOA [70], Time of Arrival (TOA) [67], [68], TDOA [69], and Received Signal Strength Indication (RSSI) [71]. These algorithms include geometric localization methods like triangulation and trilateration, as well as adjacency information and fingerprint localization methods such as adjacency-based positioning, multiliterate, and fingerprint recognition [85]. The algorithms associated with the other four types of physical signals (Computer Vision, LiDAR, IMU, VLC) used for IPS implementation were also summarized.

Despite the extensive research on IPS technologies in warehouse environments, several critical gaps remain. First, while many studies emphasize technology adoption, there is limited focus on how these technologies address the specific challenges of dynamic inventory management in large-scale warehouses. Second, the trade-offs between cost, precision, and scalability are often overlooked, leading to a lack of practical guidance for technology selection. Third, few studies explore hybrid solutions combining multiple IPS technologies to balance their strengths and limitations. These gaps underscore the need for tailored evaluation frameworks and innovative approaches to optimize IPS deployment for inventory management.

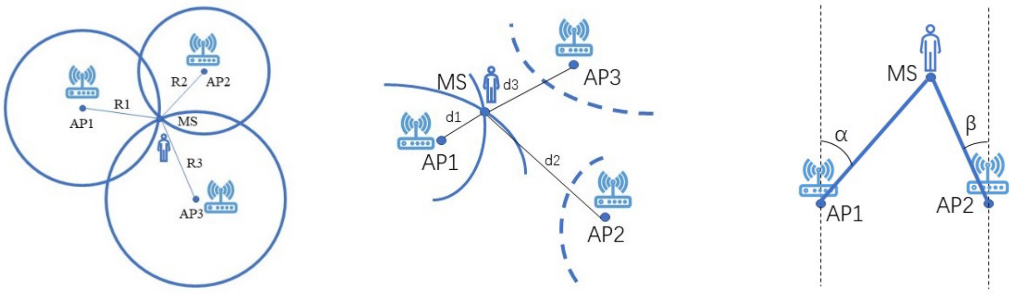
Table 9. Overview of common wireless localization methods and principles

Methods		Described	References
Geometric Measurement	TOA	Determination of position by measuring the propagation time of a signal from transmitter to receiver.	[67]
	TDOA	Determination of position by measuring the time difference between signal arrivals at multiple receivers with known positions.	[69]
	AOA	Determines position by measuring the AOA of the signal using an antenna array or directional antenna on the receiver.	[70]
Fingerprinting	RSSI (RSS)	The fingerprint localization method establishes a correspondence between the geographic location of each point in the indoor space and the signal. It achieves positioning through feature matching.	[70], [71]

3.3.3.1 Wi-Fi-based IPS technology

The principle of active positioning in Wi-Fi-based positioning is established by placing a certain number of Access Points (APs) in the indoor environment. When the mobile receiving end enters the positioning area, a search for the APs to transmit wireless signals is initiated, and location is determined through the received signal values, as shown in Figure 9. Currently, mainstream Wi-Fi positioning technologies fall into two categories: active Wi-Fi localization technologies that utilize geometric measurements and passive positioning technologies based on Wi-Fi fingerprint information [66]. The categorization of Wi-Fi-based IPS technologies is presented in Table 9. In geometric measurement-based Wi-Fi positioning technology, the distance from the receiving device to each wireless AP is calculated, and the target position is determined through distance intersection. However, the accuracy of distance measurement using Wi-Fi signals is compromised, as Wi-Fi signals are not explicitly designed for positioning. The performance of the Wi-Fi positioning method based on geometric measurement is negatively affected in indoor environments due to signal multipath, reflection, and refraction. Additionally, Wi-Fi positioning technology is susceptible to variations in signal strength. Active positioning schemes that rely on single wireless technologies, such as Wi-Fi, UWB, and RFID, include TOA [67], TDOA [69], and AOA [70], as shown in Figure 10.

Figure 9. Schematic diagram of Wi-Fi-based IPS principle



(a) (b) (c)

Figure 10. Active wireless location method: (a) TOA, (b) TDOA, and (c) AOA

The measurement object of both TOA and TDOA methods is the time signals are disseminated. By multiplying the speed of the signal by the TOA data, the relative distance between the signal source and the measurement point can be calculated. Therefore, the crux of the method lies in the accurate acquisition of signal propagation time. A mechanism to improve TOA or AOA localization performance by transmitting multiple predefined messages was proposed by Yang et al. [68], allowing for reduced network bandwidth and antenna requirements while maintaining high-accuracy performance. In a study by Cheng et al. [72], the Taylor algorithm was developed, achieving 1-decimeter positioning accuracy in indoor line-of-sight (LOS) environments with dynamic and static data. The AOA-based ranging positioning method relies on the angle between the target and at least two known positions to pinpoint the target's location. A robust phased array-based positioning system, which adopts a sparse reconstruction algorithm to improve AOA algorithm accuracy significantly, was proposed by Gong et al. [73]. In 2020, Vashist et al. introduced an indoor warehouse location system using a 60GHz wireless router and SNR as a feature of consumer-grade wireless APs in a machine learning-based location algorithm. The system achieved Remarkable centimetre-level accuracy with an RMSE of 0.84m and an MAE of 0.37m, meeting the accuracy requirements for warehouses [58].

In the realm of passive Wi-Fi positioning technology based on fingerprint information, the following concept applies: Wi-Fi fingerprint localization is predicated on the correspondence between the geographic location of each point in indoor space and the signal, achieving positioning through feature matching, as depicted in Figure 11. Indoor environments are partitioned into several blocks, each possessing a unique "fingerprint," which encapsulates the characteristic information of the location and other features that constitute part of the "fingerprint library" [68]. Two signals are primarily relied upon in fingerprint localisation methods: RSSI and CSI. RSSI represents a quantized measurement of the physical signal strength received, known as RSS, and is utilized in various wireless applications. CSI provides a more comprehensive assessment of channel conditions between the transmitter and receiver. The establishment of an accurate channel attenuation model is identified as critical for RSSI-based ranging and positioning algorithms. A wireless map with fine-grained CSI was established by Shi et al. [74] to improve target location estimation accuracy. The SpotFi system, proposed by Hoang et al. [75], utilized a convolutional neural network (CNN) to train signal features, thereby enhancing the accuracy of RSSI measurement. A deep learning model equipped with an attention module was employed by Brunello et al. [76] for the first time, improving fingerprint-based IPS in both theoretical aspects and localization accuracy, achieving a range of 0.8-1.0 m in accuracy.

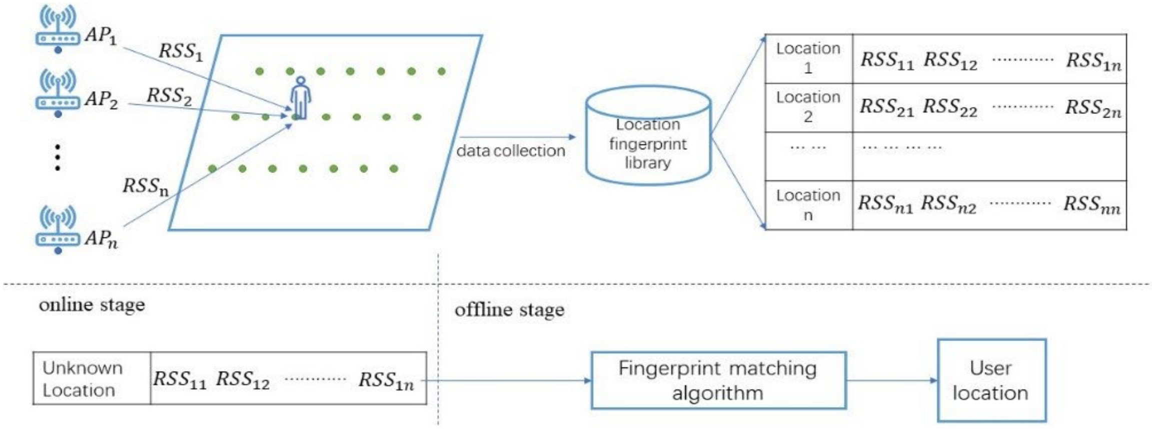


Figure 21. Schematic representation of the fingerprinting localization method for Wi-Fi-based indoor positioning

In summary, geometry-based active Wi-Fi positioning techniques are constrained by their low accuracy in indoor environments affected by signal multipath, reflection, and refraction, as well as their susceptibility to fluctuations in signal strength. Based on the literature surveyed, the challenge lies in obtaining accurate signal propagation times through improved algorithms or device performance. Passive Wi-Fi positioning techniques based on fingerprint information face limitations, such as the significant effort required to build an offline fingerprint database and the difficulty adapting to environments undergoing substantial changes. Establishing an accurate channel fading model is a challenge for RSSI-based ranging and positioning algorithms.

3.3.3.2 UWB-based IPS technology

The US Department of Defense first proposed UWB technology in the 1960s, and it was primarily utilized for military applications at that time [77]. It wasn't until 1998 that the Federal Communications Commission (FCC) authorised civil use of the technology. UWB technology utilizes an extensive frequency band, ranging from 3.1 to 10.6 gigahertz, by transmitting very short pulses, thus providing significant bandwidth advantages and short pulse periods. As a result, UWB can offer greater capacity and higher data rates. In addition, it performs well in low signal-to-noise ratio communication channel conditions and is immune to multipath propagation conditions. This makes UWB communications suitable for indoor positioning applications [78], especially in non-line-of-sight (NLOS) conditions. Since the transmission is in short pulses, UWB signals are transmitted with a low average power spectral density, placing them on the noise floor (typically -40 dBm/MHz), resulting in reduced transmit power consumption, improved power efficiency, and resistance to interference and interception, as shown in Figure 12 [122].

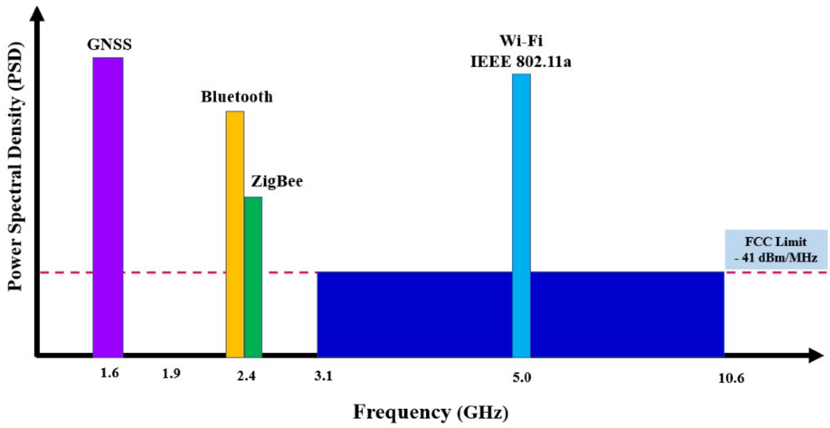


Figure 12. Comparison of UWB spectral properties with various positioning techniques [122]

UWB technology shares similarities with Wi-Fi regarding technical routes, as both utilize wireless signals for positioning. However, their characteristics and application scenarios differ. Like UWB, Wi-Fi can achieve positioning through methods such as RSSI, TOA, or AOA, as shown in Figure 10 and Figure 11. Nevertheless, UWB employs ultra-wideband frequencies and short-pulse transmission, providing higher precision and stronger resistance to multipath effects than Wi-Fi's narrowband communication, especially in non-line-of-sight (NLOS) environments. Meanwhile, Wi-Fi, with its widespread infrastructure deployment and lower costs, is better suited for large-scale indoor coverage scenarios. Thus, while UWB and Wi-Fi share overlapping principles, the former focuses more on high-precision and low-latency positioning requirements, whereas the latter emphasizes accessibility and cost efficiency. The two technologies exhibit a complementary relationship in indoor positioning applications.

In UWB-based geometric measurements, the primary focus of researchers has been on error reduction in NLOS environments, where obstacles can obstruct the direct path between the transmitter and receiver, leading to signal reflection, diffraction, or scattering. A machine learning-based algorithm for classifying signal propagation in LOS and NLOS situations was developed by Marano et al. [79], effectively reducing the resulting errors. The variation law of residuals between LOS and NLOS indoor environments was studied by Zhang et al. [80] using the Kalman Filtering algorithm (KF). NLOS errors were identified and mitigated by setting an appropriate threshold and comparing real-time residuals with ranging. Yu et al. [81] corrected signal arrival time estimation when UWB signals propagated in complex indoor NLOS environments. A method for NLOS error elimination based on TOA was proposed by Go et al. [82], where the distance measurement value of the signal propagation between different base stations and tags performs the distance compensation. An algorithm that combines the least squares method and the Kalman Filter algorithm was introduced by Wang et al. [83], demonstrating a positioning accuracy of 9.3 cm. Research into UWB-based fingerprint positioning methods has included techniques to reduce positioning errors from NLOS and multipath effects. Channel measurement [85], front-end energy sampling on the receiving end [86], and measurement error noise are commonly utilized techniques. A new UWB positioning system based on an unmanned aerial vehicle (UAV) using integrated Radio Frequency (RF) hardware and antennas was proposed by Tiemann et al. (2015) [87]. The challenges of achieving accurate UAV localization in large warehouses were discussed by Macoir et al. [84], especially considering the high costs associated with deploying complex wiring and power infrastructures required by large-scale UWB systems.

High measurement accuracy is one of the main advantages of UWB positioning technology, with location errors reported to be less than 10cm in some instances [83]. Good multipath mitigation is also offered by UWB, making it suitable for environments with high-density tags and high mobility. However, limitations of UWB positioning technology include the time-consuming and expensive initial setup, which requires precise calibration and placement of transceivers, and the need for an unobstructed path between the transmitter and receiver. These limitations can compromise its effectiveness in specific indoor environment settings. UWB is widely used in warehouse environments for inventory tracking, AGV navigation, and real-time personnel monitoring. For instance, UWB-based positioning systems have been implemented to enable high-precision tracking of goods on high shelves, ensuring inventory accuracy while minimizing manual intervention. Moreover, UWB's ability to provide robust performance in high-mobility scenarios has been leveraged for AGVs, where its low latency and high accuracy are critical for collision avoidance and optimal path planning.

UWB technology excels in indoor positioning with high accuracy, strong NLOS performance, and resistance to multipath effects, making it ideal for inventory tracking and AGV navigation tasks. However, it faces challenges such as high deployment costs, complex calibration, and scalability issues in large-scale environments. To overcome the inherent limitations of UWB, researchers have explored its integration with other positioning technologies. For example, UWB-LiDAR fusion systems have enhanced 3D mapping and navigation accuracy, particularly in cluttered indoor environments [60]. Although these hybrid systems improve performance, they also increase complexity and costs. Future advancements in UWB technology focus on simplifying deployment and reducing costs by utilizing software-defined systems equipped with real-time calibration and adaptive algorithms. Additionally, integrating AI is anticipated to enhance NLOS error mitigation and boost signal reliability, further broadening UWB’s robotics, smart warehouses, and healthcare applications.

3.3.3.3 RFID-based IPS Technology

Derived from the rapid development of radar communication technology in the 1950s, RFID is a non-contact method for transmitting information. Utilizing RF signals through spatial coupling, this technology serves the purpose of automatic identification [88]. Over the years, substantial advancements have been made in the technical theory of RFID. Initially applied in the field of indoor positioning since the start of this century, RFID has given rise to classic positioning systems like the SpotON [89], LANDMARC system [90], and VIRE system [91]. As shown in Figure 13, RFID tags are deployed on the ground in a specified pattern for RFID-based positioning. The ID information of an RFID tag is tied to its coordinate position on the ground, so RFID-based e-maps can be defined based on the tag's ID and position [123]. The LANDMARC system operates by deploying a network of fixed reference points, such as access points or RFID readers, throughout indoor areas. These reference points are anchors for measuring the wireless signals emitted by mobile devices or tags carried by individuals or objects. Several modifications and enhancements to the LANDMARC system have been proposed to address the complexity of indoor environments. Gu et al. (2020) introduced a novel indoor positioning algorithm based on LANDMARC to balance cost and precision. The system replaced physical tags with "reference tags," reducing electromagnetic interference and system costs. Furthermore, Hu et al. [90] proposed an optimized LANDMARC positioning algorithm to mitigate significant differences in RSS between tags situated close to the reader [92].

However, conventional methods like LANDMARC and K Nearest Neighbors (KNN) often suffer from limited accuracy due to signal reflection, diffraction, and non-occlusion factors. Zhou et al. [93] presented an improved KNN method that corrected target coordinates using a passive RFID system. Subedi et al. [94] achieved centimeter-level localization accuracy in complex environments using only RSSI measurements from multiple passive tags. Li et al. [95]

introduced the WIMEC-LANDMARC algorithm that incorporates average error correction, improving accuracy. Additional advancements include work by Teo et al. [39], who demonstrated effective autonomous mobile robot navigation using RFID signal strength sensing. Tao et al. [123] proposed a Monte Carlo and dual-antenna joint corrective fit-based scheme, which showed significantly higher localization accuracy than particle filter-based algorithms. A recent trend involves the incorporation of intelligent algorithms into RFID-based IPS. Notably, a neural network-based optimization method was proposed, significantly improving system localization accuracy [95].

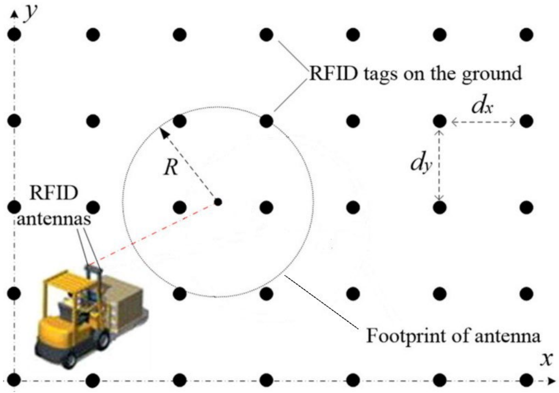


Figure 13. RFID-based Indoor positioning system

3.3.3.4 VLC-based IPS technology

Visible Light Positioning has emerged as a dual-functional technology, offering illumination and communication features. This innovative approach is gaining significant traction in the field of IPS [96]. Specifically, VLP, a subset of VLC, is identified as an up-and-coming solution for indoor positioning, as shown in Figure 14 [97]. The system is a high-precision indoor positioning solution based on a single LED lamp. It consists of an original VLP lamp paired with a small luminescent beacon mounted on its edge, which emits encoded visible light signals. Using a CMOS sensor with a rolling shutter mechanism, the system captures bright and dark stripes formed by the light signal. Image processing algorithms extract the pixel coordinates of the lamp and beacon, which are combined with the beacon's physical coordinates to calculate the precise position of the device using trigonometric functions. A beacon-searching algorithm further accelerates the localization process. The low-complexity design requires processing only a single set of bright and dark stripes without binarization or complex projections, ensuring high efficiency and low hardware requirements. The system achieves centimeter-level accuracy (average error of 2.26 cm) and millisecond-level response times (average positioning time of 6.3 ms), making it suitable for indoor navigation applications on low-cost embedded platforms.

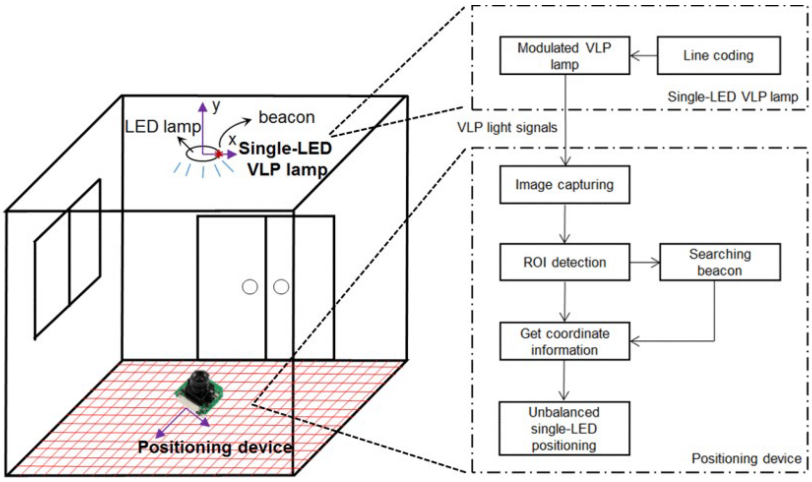


Figure 14. VLC-based IPS system architecture [97]

In recent years, Chen et al. [124] proposed a method that employed fingerprinting and an Extreme Learning Machine (ELM) to achieve high localization accuracy, robust interference immunity, and excellent real-time performance. This method reported an average 3D positioning error of just 2.11 cm. Following this, Li et al. [96] presented an unbalanced single LED VLP algorithm and a fast beacon search method. For indoor settings with a height of 3 meters, their approach yielded a positioning accuracy of 2.26 cm. Practical applications of VLC in warehouse environments were researched by Louro et al. [40] [43]. A white LED lighting system was installed on the warehouse ceiling to enable bidirectional communication between the infrastructure and vehicles. This system comprises two core elements: VLC transmitters, LED lights, and AGVs with VLC receivers. Data is transmitted by white RGB LED emitters in the LED lights and collected by VLC receivers on the AGVs. An ON-OFF keying method is employed for data modulation [40]. Three primary color white LEDs and photodetectors are utilized for the transmitters and receivers. Each LED light provides positional information to the vehicles through the adequate modulation of RGB emitters. Reliable data transmission is ensured by coding and synchronization techniques, and error detection and correction are enhanced through parity bits [43].

Table 10 highlights three key VLC-based indoor positioning methods, each leveraging unique techniques to achieve high precision and real-time performance. The Single Lamp and Beacon System stands out for its simplicity and low hardware requirements, making it suitable for low-cost embedded platforms, with an accuracy of 2.26 cm and a response time of 6.3 Ms. The Fingerprinting + ELM Method achieves the highest reported 3D positioning accuracy of 2.11 cm by using machine learning to enhance robustness and real-time performance, making it ideal for static environments requiring high precision. Similarly, the Asymmetric Single Lamp VLP Algorithm focuses on fast localization with simple hardware design, balancing cost and efficiency. The Bidirectional Communication and Navigation System integrates positioning with communication, facilitating warehouse AGV navigation by leveraging RGB LED lights and robust error correction techniques. The key advantages of VLC-based IPS include its compatibility with existing lighting infrastructure in indoor spaces, making VLP highly convenient. Additionally, in environments where wireless signals are susceptible to interference, such as hospitals with MRI equipment or factories with large electromagnetic devices, VLC-based IPS is highly applicable. VLC technology also demonstrates less susceptibility to multipath effects and interference from other wireless systems. Nevertheless, challenges are faced by VLC-based IPS, particularly in maintaining positioning accuracy in environments where light reflections, diffusion, or dynamic obstacles are present. Recent advancements in VLC technology have focused on improving signal processing using machine learning algorithms. For instance, convolutional neural networks (CNNs) have been applied to enhance the robustness of signal decoding under conditions of high ambient light interference. Additionally, hybrid systems combining VLC and Wi-Fi have been proposed, leveraging the high-speed communication capabilities of VLC with the broad coverage of Wi-Fi to create a complementary system for large-scale indoor positioning.

Table 10. Overview of visible light positioning techniques and their performance

Method	Description	Performance	Features
Single Lamp and Beacon System [96]	Utilizes a single LED lamp paired with a small beacon. A CMOS sensor captures bright and dark stripes, and trigonometric functions calculate the device's position.	Accuracy: 2.26 cm Response time: 6.3 Ms	Simple design, low hardware requirements, suitable for low-cost embedded platforms.
Fingerprinting + ELM [124]	Matches light signal features with a pre-built fingerprint database. Combines Extreme Learning Machine (ELM) to enhance accuracy and interference immunity.	3D Positioning Error: 2.11 cm	It relies on environment calibration, is suitable for fixed scenarios, and enhances stability via machine learning.
Bidirectional Communication and Navigation System [43]	It uses RGB LED lights to modulate and transmit position information. AGVs with VLC receivers enable bidirectional communication and navigation.	Accuracy: Not specified	Combines communication and positioning, high reliability, suitable for warehouse AGV navigation.

3.3.3.5 IMU-based IPS technology

Inertial Measurement Unit (IMU) positioning is a technology that achieves three-dimensional spatial position and orientation estimation through sensor fusion and is widely used in drones, autonomous driving, robotics, and indoor navigation. It relies on accelerometers, gyroscopes, and magnetometers, integrating sensor data using Direction Cosine Matrix (DCM) or quaternion methods to calculate attitude angles in real-time while correcting drift errors [98]. Accelerometers provide linear acceleration data for displacement calculation, gyroscopes measure angular velocity to estimate rotation, and magnetometers reference the Earth's magnetic field to determine heading. To address cumulative errors caused by traditional double integration, jerk integration is employed for displacement calculation, and Extended Kalman Filter (EKF) further refines multi-sensor state estimation. Barometric pressure sensors or laser rangefinders assist in altitude measurement, enabling comprehensive 3D localization [99]. Despite its low cost and operational convenience, indoor positioning technology based on inertial navigation is subject to inevitable accumulated errors and requires per iodic calibration through external information. Consequently, research focused on attitude update algorithms for this system has garnered considerable attention. The Pedestrian Dead Reckoning (PDR) algorithm, a method that uses inertial sensors to calculate the distance and direction of a target's movement, was first proposed by Wu et al. [100]. This method enables the calculation of the target's relative position. Figure 15 illustrates the general framework of an IMU-based Pedestrian Dead Reckoning (PDR) system, providing a comprehensive depiction of the process from sensor data collection to trajectory output. The system is centered on accelerometers, gyroscopes, and magnetometers, which measure linear acceleration, angular velocity, and geomagnetic direction, respectively, with barometers optionally used for altitude variation measurement. In the preprocessing stage, features are extracted through gait detection and motion classification. Gait detection leverages methods such as Zero-Velocity Update (ZUPT) and Zero-Angular Rate Update (ZARU) to identify gait phases. At the same time, motion classification employs machine learning algorithms to distinguish motion types (e.g., walking, running), ensuring high-quality input for trajectory calculation.

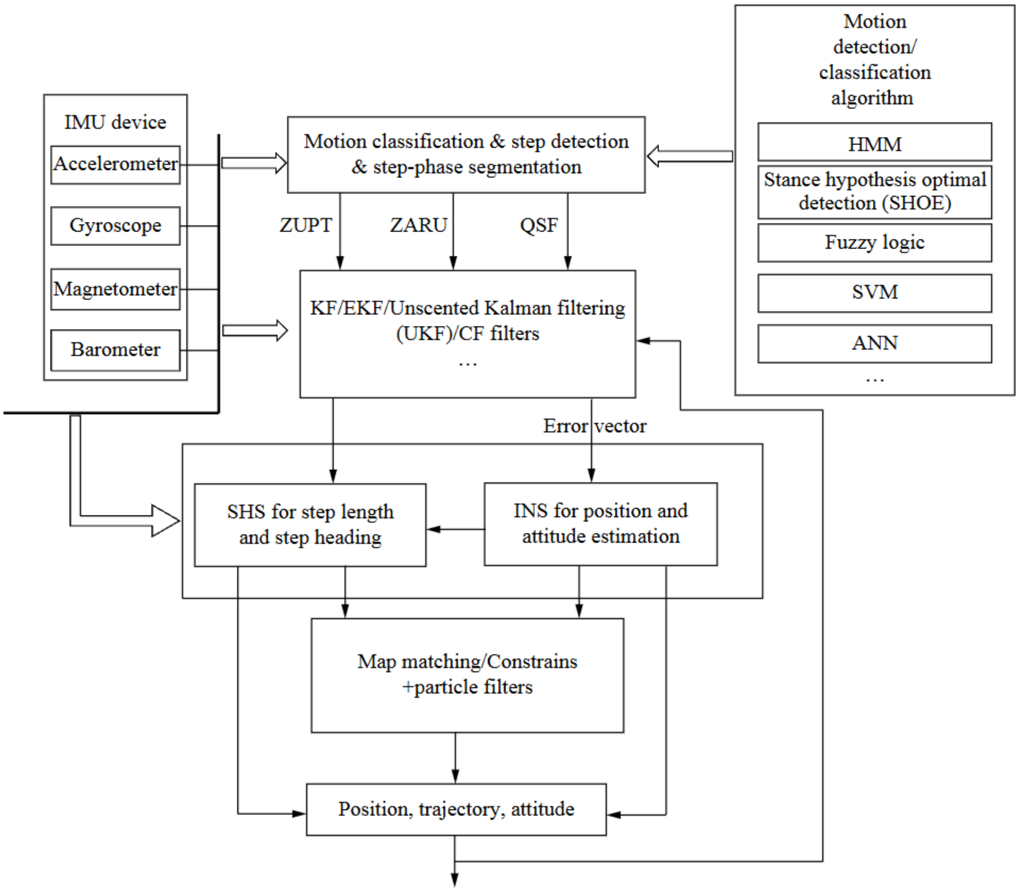


Figure 15. IMU-based pedestrian dead reckoning system framework [100]

The core algorithms include Inertial Navigation Systems (INS) and Step-and-Heading Systems (SHS). INS estimate positions through integration while combining ZUPT and EKF to mitigate error accumulation. SHS calculates trajectories by incrementally adding step lengths and headings. Map matching and magnetic field correction also constrain trajectory errors, enhancing accuracy. Ultimately, the system outputs high-precision three-dimensional positions, trajectories, and orientation information. Through modular design, data fusion, and environmental constraints, this framework effectively addresses error issues in inertial navigation, providing a reliable solution for indoor positioning. Recent advancements in IMU-related algorithms have focused on improving positioning accuracy in dynamic and cluttered warehouse environments. For instance, Tong et al. [101] proposed an Enhanced PDR algorithm optimized for AGV navigation in high-density storage areas, achieving a 15% reduction in cumulative error compared to traditional methods. To mitigate the cumulative error inherent in IMU-based positioning, hybrid systems integrating IMU with Simultaneous Localization and Mapping (SLAM), LiDAR, or vision-based technologies have gained significant traction. For example, in a study by Qin et al. [113], the VINS-Mono system combined IMU with monocular vision to achieve precise localization in dynamic warehouse environments, demonstrating long-term operational stability with a maximum error of 8 cm under the EuRoC dataset. Similarly, Kim et al. [61] proposed a method for calibrating IMU and LiDAR pairings, enabling robust navigation in cluttered warehouse spaces. These hybrid systems leverage the complementary strengths of IMU and other sensors, significantly improving positioning accuracy and reliability in complex indoor environments.

In conclusion, IMU-based indoor positioning is widely adopted in navigation and positioning equipment due to its cost-effectiveness, compact design, and ability to operate independently of external signals. This autonomy makes IMU systems particularly suitable for complex warehouse environments characterized by narrow aisles, high-density storage, and dynamic obstacles, where reliable and precise localization is critical. The development of Micro-Electro-Mechanical Systems (MEMS) has further enhanced the precision and reliability of IMU-based systems in indoor settings. However, challenges such as cumulative errors and sensitivity to external disturbances necessitate periodic calibration and algorithmic improvements. To address these issues, researchers are focusing on adaptive filtering techniques, enhanced sensor fusion methods, and the integration of IMU with technologies such as SLAM and LiDAR, which have demonstrated significant potential in improving positioning accuracy and robustness. Future advancements in real-time data fusion and error correction algorithms are expected to expand the applicability of IMU-based systems, making them a vital component of intelligent warehouse operations.

3.3.3.6 Computer vision-based IPS technology

Computer vision technology was developed with advancements in sensor devices, computer computing power, and image processing technology. Since the 1980s, machine vision technology has been extensively researched. Techniques for vision-based positioning, including monocular vision, binocular vision, and RGB-D, are included. The process flow for obtaining environmental image information through the camera lens in computer vision positioning technology is illustrated in Figure 16. Firstly, images are captured by a calibrated camera [125], then image processing and analysis are performed, and finally, the required information about the external environment is derived. Computer vision-based IPS technology can be classified into known and unknown environments according to the prior information of the environment possessed by the receiving device [102].

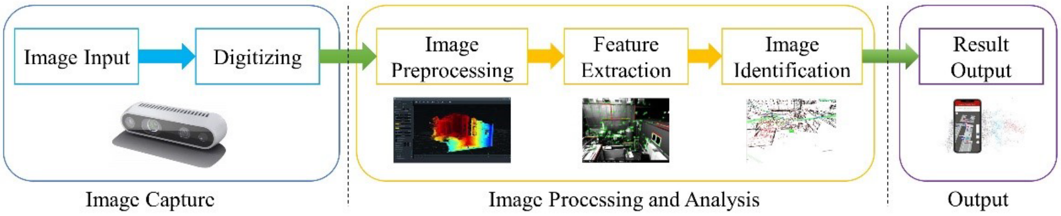


Figure 16. Process flow of computer vision positioning technology

In known environments, the location of equipment is established based on image data captured by a camera using visual positioning technology. Previously mapped environments with features such as artificial beacons or markers are referred to as known environments. During the localization process, the captured image is matched with images or markers stored in a database and location information is obtained from the most similar image. The first introduction of computer vision for indoor positioning was made by a mobile robot designed by Kriegman et al. [103]. Linear geometric features were extracted from images captured by a monocular camera on the robot, and the extended Kalman filter was used to reduce uncertainty and determine the camera position. Since then, various approaches for optimizing feature extraction methods and improving localization performance have been proposed. Simultaneous Localization and Mapping, a widely used technique in robotics and indoor navigation, has further advanced the integration of computer vision into indoor positioning systems. SLAM enables a device to construct a map of an unknown environment while simultaneously localizing itself within that map. The SeqSLAM method, proposed by Milford et al. [104], uses image differences to measure similarity between images and improves localization accuracy through graph matching. Vehicle speed and distance were estimated by an algorithm presented by Ho et al. [105] utilizing a monocular camera to measure optical flow and control inputs. The robustness of image recognition was enhanced by a place recognition method based on LDB (Local Difference Binary) features proposed by Arroyo et al. [106]. A neural network called NetVLAD for extracting image features was proposed by Arandjelovic et al. [107], using a large amount of image data to learn representations for VLAD (vector of locally aggregated descriptors) features [108].

In unknown environments where existing beacon methods are not applicable, the environment is reconstructed through real-time and online video. The position of the image sensor is calculated in real-time using Visual Simultaneous Localization and Mapping technology [102]. Feature point associations between two images are established by extracting and matching image feature points. Peripolar geometry is used to solve camera motion, and triangulation is used to calculate the 3D information of features [109]. Davison developed a SLAM technology positioning system based on monocular vision in 2003, combining the SLAM algorithm with visual positioning technology [126]. ORB-SLAM, a robust positioning system for locating vigorously moving targets, was proposed by Mur-Artal et al. [110]. Support for different vision devices and fully automatic initialization were added in the ORB-SLAM2 [111] and ORB-SLAM3 [112] systems, developed in 2017 and 2021, respectively. The components of ORB-SLAM1, ORB-SLAM2, and ORB-SLAM3 are depicted with different background colors to indicate their version-specific functionalities in Figure 17. ORB-SLAM1 centers on TRACKING, LOCAL MAPPING, and LOOP CLOSING modules for basic navigation and mapping. Additional features in ORB-SLAM2 include support for more camera types and enhanced accuracy [111]. ORB-SLAM3 introduces IMU integration and the Atlas module for advanced map construction and localization, increasing accuracy across varied scenes.

Hardware constraints and the ever-expanding range of positioning targets impose significant limitations on the localization accuracy of pure visual SLAM. Consequently, the development of multi-sensor positioning systems that incorporate vision technology, inertial navigation, LiDAR, and wireless communication technology has been deemed necessary. Such a system is the VINS-Mono, developed by Qin et al. [113], in which localization is achieved by integrating vision and inertial navigation IMU devices. High stability, contributing to long-term operational accuracy and robustness, is exhibited by the VINS-Mono and VIN-Mobile systems. Under the EuRoC data set, a maximum error of 8 cm in the localization accuracy of the VINS-Mono system is recorded. A system that combines computer vision and Lidar was proposed by Mohta et al. [50], enabling rapid and reliable autonomous navigation even with limited prior environmental knowledge. This system achieves a maximum speed of 7 m/s and a final position drift of less than 2 m. The lowest-cost navigation platform for unknown cluttered environments to date has been implemented by Campos-Macías et al. [114] using the Intel Ready to Fly drone kit. Overall, computer vision-based indoor navigation technology promises accurate and real-time positioning in indoor environments. One of its main advantages is that no additional infrastructure or hardware installation is required, rendering it cost-effective and easy to deploy. Suitability for low-light conditions is another advantage. However, drawbacks exist, such as the requirement for high computational power, which may limit real-time performance. Additionally, accuracy may be influenced by the quality and quantity of visual features in the environment.

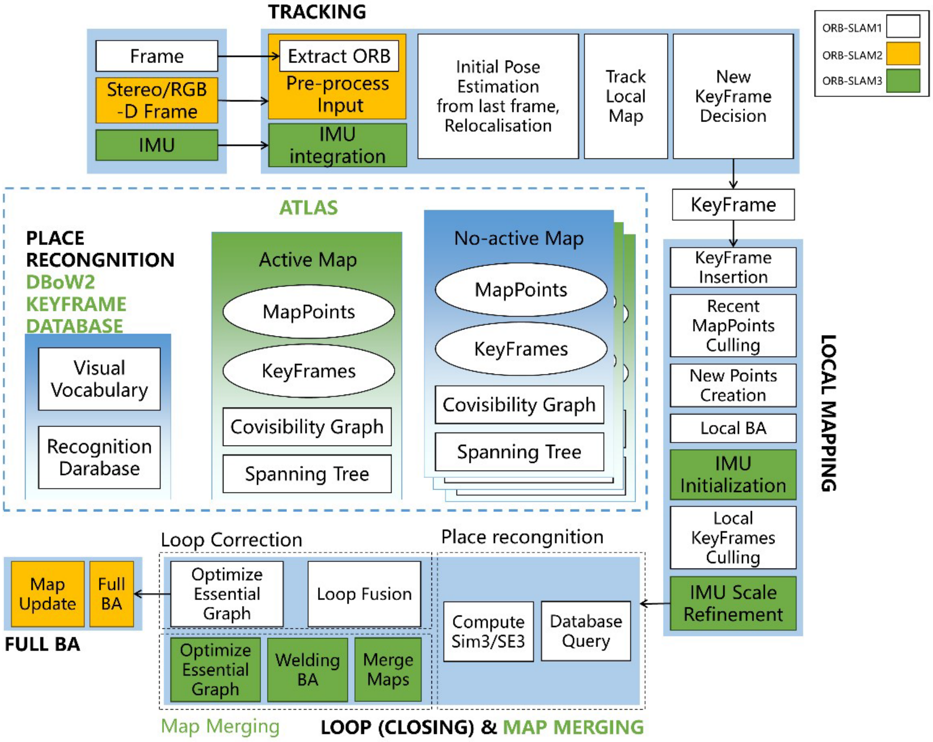


Figure 17. The main system components of ORB-SLAM1-3 and their enhancements

3.3.3.7 LiDAR-based IPS technology

LiDAR (Light Detection and Ranging) is identified as a sensing technology in which lasers are employed to measure distances and construct precise 3D models of an area. Its capacity to operate in GPS-denied and weak signal indoor settings has contributed to its broad adoption for indoor positioning due to its accuracy and reliability in recent years [115]. In LiDAR indoor positioning technology, laser beams are emitted in all directions by a LiDAR sensor. These beams are bounced back upon encountering objects, and the Time-of-Flight between emission and return is analyzed to calculate the object's distance and position. This process is repeated multiple times, culminating in a large point cloud data set that represents the 3D environment. Technology has facilitated integration with the specific requirements of various fields, leading to its extensive application in diverse domains [116].

SLAM utilizing LiDAR technology has been recognized as a significant research direction in mobile robotics [111]. As illustrated in Figure 18, the basic framework of a LiDAR-based SLAM system consists of several key components that work together to achieve accurate localization and mapping. First, "data sensing" is handled by the LiDAR sensor, which emits laser beams to capture point cloud data representing the surrounding environment. This raw data is processed in the next stage, where "data processing and estimation" are managed by the odometer. The odometer estimates the sensor's position and orientation by aligning successive scans using Iterative Closest Point (ICP) algorithms. Subsequently, "global map construction" optimizes the alignment of multiple scans across a larger area, correcting cumulative errors and ensuring consistency in the 3D map. Finally, "loopback detection" identifies previously visited locations, aligning them with current scans to eliminate drift and enhance overall map accuracy, particularly during extended mapping sessions. Among its advantages is the technology's functionality in GPS-compromised environments, such as warehouse environments. LiDAR-based IPS technologies are widely utilized for inventory management, automated guided vehicle navigation, and high-density shelving structural inspection. Generating precise 3D models enables LiDAR-equipped AGVs to navigate complex warehouse layouts accurately, avoiding obstacles and optimizing path planning in real-time. LiDAR sensors mounted on UAVs have also been employed for inventory inspections in elevated storage areas, providing centimetre-level accuracy in locating and auditing goods. These applications highlight LiDAR's unparalleled ability to address the challenges of high-density, dynamic warehouse environments.

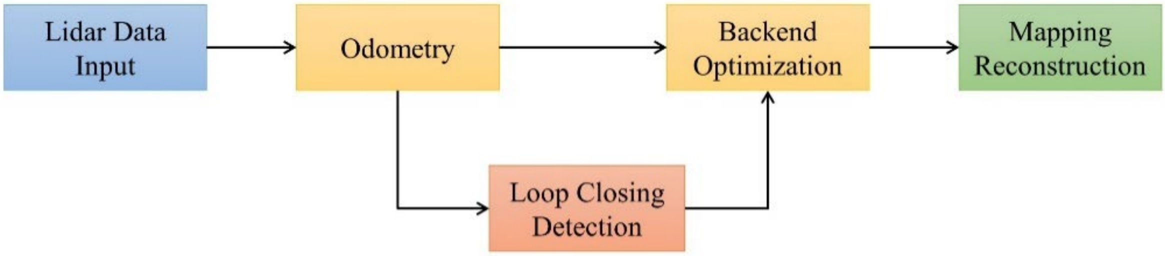


Figure 18. Basic framework for SLAM

Several challenges exist in employing LiDAR for indoor positioning, including data processing and noise filtration. Various researchers have tried to enhance the accuracy of LiDAR for indoor positioning. A method combining motion models with LiDAR measurement data was proposed by Sánchez et al., which uses infrastructure elements as positioning references. Wang et al. [117] presented an efficient algorithm that employs LiDAR as the sole environmental detection sensor in IPS research, thus reducing computational effort while preserving localization robustness [118]. Recent advancements in LiDAR-based IPS systems have focused on improving point cloud data processing and reducing computational overhead. For instance, Shi et al. [119] proposed a lightweight SLAM algorithm that achieves real-time performance in high-density storage environments, reducing latency by 30% compared to traditional SLAM methods. Hardware innovations, such as the development of low-cost solid-state LiDAR sensors, are also expanding the accessibility of LiDAR technology in cost-sensitive warehouse applications. Two commercially available solid-state LiDAR SLAM frameworks with mature technology currently exist: the FAST LOAM framework [120], and the LOAM Livox framework [121]. A multi-sensor fusion framework was put forth by Kwon et al. [25] to facilitate practical autonomous UAV navigation in GPS-deprived, poorly lit warehouses, albeit at a relatively high cost.

Future research on LiDAR-based IPS systems is expected to explore further integrating artificial intelligence (AI) techniques to enhance system adaptability and efficiency. Deep learning algorithms can process point cloud data, enabling more accurate object recognition and anomaly detection in warehouse environments. Additionally, the combination of LiDAR and predictive analytics may facilitate proactive maintenance and inventory forecasting, paving the way for fully autonomous and intelligent warehouse operations. In summary, the analysis of IPS technologies highlights their transformative impact on inventory management within warehouse environments. With its scalability and cost-effectiveness, RFID is widely used for ground-level inventory tracking and bulk item identification. UWB stands out for its high precision and adaptability in dynamic inventory tasks, ensuring real-time updates even in complex and densely packed storage areas. LiDAR offers unparalleled 3D mapping capabilities, particularly suited for high-density and elevated inventory spaces. At the same time, Wi-Fi provides an accessible and cost-sensitive option for smaller warehouses or less complex layouts. These technologies collectively address critical challenges in inventory management, such as accuracy, real-time tracking, and scalability. Their integration improves operational efficiency and automates traditionally manual processes, reducing errors and optimizing resource utilization. As inventory management is the foundation for other warehouse operations, the strategic deployment of IPS technologies in this domain ensures broader improvements in overall warehouse productivity.

3.4 RQ3: How can different IPS technologies for logistics management applications in a warehouse environment be evaluated?

From the analysis in the preceding section, it is understood that IPS systems in warehouse environments feature a wide range of technologies. Classical positioning techniques are continuously evolving, and new technologies are emerging. Establishing an evaluation framework for IPS systems in warehouse environments would assist significantly in comprehending the development in this area. It would provide substantial assistance to engineers engaged in related projects. This section aims to summarize key metrics for various indoor positioning techniques and propose a comprehensive and comparable evaluation framework for applying indoor positioning technology based on these metrics. Unlike existing frameworks, which often generalize across warehouse tasks, this framework emphasizes criteria directly tied to inventory management, such as real-time accuracy, adaptability to dynamic environments, and cost-effectiveness.

A review of five papers on indoor positioning technology [54] [127], [128], [129] underscores the significance of classification methods and evaluation metrics for establishing IPS systems. An assessment system that considers energy efficiency, cost, availability, reception range delay, scalability, and tracking accuracy was proposed by Zafari et al. [54]. Seco et al. [127] classified indoor positioning systems into four categories: geometry-based methods, minimization of the cost function, fingerprint localization, and Bayesian techniques. A division of positioning systems into 13 categories based on technical characteristics was systematically undertaken by Mautz et al. [128]. Detailed summaries of two review papers proposing evaluation frameworks for indoor positioning systems have been compiled. Performance benchmarking for indoor wireless location systems, including accuracy, precision, complexity, scalability, robustness, and cost, was provided by Liu et al. [130]. In Liu's paper, evaluations of the IPS systems were conducted using specific data and metrics. Zafari et al. [54] identified several key challenges in indoor localization and incorporated them as the main indicators in their evaluation framework. While researchers have proposed various classification criteria or evaluation frameworks for indoor positioning technologies, many are designed for general academic research. In contrast, this study focuses on comprehensive evaluation criteria tailored explicitly for the warehouse environment.

Table 11. IPS application evaluation metrics

Metrics	Description	Evaluation method
Applicability	Using easily accessible technology that does not require specialized hardware on the user's end is crucial for widespread adoption.	The amount of equipment and effort needed for deploying different indoor positioning technologies is compared, and applicability is evaluated as low, medium, or high.
Accuracy	The most critical aspect of a positioning system is the accuracy with which the user/device position is obtained. In the papers surveyed, the focus is predominantly on localization accuracy. Consideration for other functions or parameters is only given if accuracy is satisfactory.	Data evaluation
Cost	While most positioning systems surveyed are in laboratory environments and rarely mention the cost. In this study, it is believed that high-precision positioning significantly increases system cost. Widespread consumer market adoption requires reasonable cost control.	Cost assessment is based on a uniform applicable area within the same indoor positioning scenario. Market economic factors are considered mainly, and only the official selling price of the main equipment is used for relative evaluation as low, medium, or high.
Energy Efficiency	The design of a positioning system must prioritize power efficiency to enable extended operational periods without draining the device's battery. Therefore, reducing energy consumption is essential for the system's prolonged stability and reliability.	The sum of the power consumption of major equipment is considered. Evaluations are made based on low, medium, or high energy efficiency.
Scalability	The system's scalability and applicability are considered essential.	Uncertain factors that might arise during the use of the technology and their consequences are considered in the evaluation, which is measured as low, medium, or high.

In general, scholars have undertaken substantial discussions on how to evaluate IPS systems. ISO/IEC 18305:2016 International Standard, which identifies appropriate performance metrics and test & evaluation scenarios, also provides guidance on the best ways to present and visualize T&E results. However, a critical review of this standard was conducted by Potorti et al. [131], who believe many indicators are unsuitable for direct user applications. A perspective that IPS must be low-cost, low-power, and require a minimal amount of new infrastructure was expressed by Wirola et al. [132]. Performance metrics proposed in the reviewed articles have been synthesized, and popular research areas indicated in Figure 6 have been considered. Metrics of limited evaluation value in the warehouse environment, such as "robustness," have been excluded and merged into the "scalability" metric. Primary indicators more suitable for evaluating IPS in the warehouse environment, including "applicability," "accuracy," "cost," "energy efficiency," and "scalability," have been selected. The evaluation methods for these metrics are summarized in Table 11.

To comprehensively evaluate IPS technologies for inventory management, this study compares RFID, UWB, LiDAR, IMU, Wi-Fi, VLC and Computer Vision across several critical dimensions: precision, cost, scalability, and environmental adaptability. These dimensions are essential for ensuring that selected technologies align with the specific requirements of inventory management tasks. UWB provides the highest precision, with localization errors typically below 10 cm, making it ideal for dynamic inventory tasks in large or multi-level warehouses. LiDAR offers comparable precision in static or semi-static environments, particularly high-density storage spaces. RFID and Wi-Fi, while less precise, are effective for routine stocktaking and bulk inventory identification tasks. RFID and Wi-Fi are the most cost-effective options, suitable for budget-constrained implementations or smaller warehouses. UWB and LiDAR, although more expensive, justify their higher costs with superior performance in high-complexity scenarios where precision and adaptability are paramount. Its high cost and environmental sensitivity limit LiDAR's scalability, while Wi-Fi scalability depends on robust network infrastructure. This comparative analysis highlights that no single IPS technology universally outperforms others; instead, its effectiveness depends on the specific priorities and constraints of the inventory management task. For instance, UWB is best suited for high-precision dynamic tracking, whereas RFID offers an optimal solution for large-scale, cost-sensitive implementations. These trade-offs underscore the importance of selecting technologies based on task-specific needs, as shown in Tables 12 and 13. In summary, comprehensive data analysis and compilation based on 38 selected articles are presented, addressing the RQs, providing substantial data support for the subsequent discussions, and providing insights into the field of IPS in warehouse environments.

Table 12. Comparison of IPS technologies in warehouse environments

Tech.	Evaluation Framework					References
	Applicability	Accuracy	Cost	Energy Efficiency	Scalability	
Computer Vision	High	High	Medium	Low	High	[23],[37],[64] [50],[61],[25] [49],[30],[44] [45],[35],[33]
LiDAR	Medium	High	High	Medium	Medium	[23],[64],[24] [61],[25],[52] [41],[51],[42] [65],[45],[46]
RFID	Medium	Low-Medium	Low	Low	Low	[39],[27],[29] [63],[31],[48] [32],[47],[34]
UWB	Low	High	Medium	Low	Medium	[38],[26],[59] [60]
Wi-Fi	Low	Medium-High	Medium	Medium	Medium	[58],[28],[57]
IMU	Medium	Medium	Low	Low	Low	[61],[42]
VLC	Medium	Low	Low	Low	Low	[40],[43]

Table 13. Advantages and limitations of IPS technologies

Tech.	Advantages	Limitations
Computer Vision	Current vision SLAM technologies offer higher accuracy. Less reliance on external environment modifications is needed for positioning. Scalability in more complex and dynamic environments is provided. Object detection and tracking capabilities are present.	Computational requirements are high, and much arithmetic support is needed. Positioning accuracy may be affected by external lighting conditions when using ordinary monocular or binocular cameras. Coverage is limited, generally within 10 meters, and line-of-sight is required.
LiDAR	Distance to the target point is measured more accurately using TOF technology. A larger measurement distance and coverage area are provided. Strong adaptability in different lighting conditions is observed.	High costs. Object detection on transparent or reflective surfaces may lack accuracy. Large amounts of point cloud data require processing. A direct line-of-sight to objects is needed for sensing.
RFID	NLOS tracking is enabled and suitable for complex and obstructed environments like warehouses. Costs are relatively low, especially for warehouse deployments.	Positioning accuracy is limited. The detection range for RFID tags by the reader is limited. Performance may be affected by environmental factors such as metal surfaces, liquids, and electromagnetic interference.
UWB	High-precision positioning within a few centimetres is achieved. UWB signals can penetrate obstacles due to high adaptability to complex environments. Power consumption is relatively low.	The range is limited. Initial setup may require careful planning and calibration, increasing the up-front workload. High initial costs may be incurred.
Wi-Fi	Wide coverage is typically provided in various indoor environments. Existing Wi-Fi infrastructure is utilized, making it cost-effective. Large areas can be covered, and signals can penetrate obstacles.	Interference and signal variations may occur in environments with high device density. Signal transmission faces challenges such as attenuation, reflections, and multipath interference. Reliance on the availability and coverage of Wi-Fi access points exists.
IMU	Real-time motion tracking and orientation information for continuous positioning updates are provided. Independence from external infrastructure is achieved. High-frequency data updates are offered to track fast-moving objects.	Measurement errors and drift over time result in accumulated positioning errors. Only relative positioning information is provided. Sensitivity to external factors like magnetic fields, temperature variations, and vibrations is high.
VLC	Existing indoor lighting infrastructure can be utilized, eliminating the need for specialized hardware. Operation in the visible spectrum results in less interference. High data rates for real-time positioning updates are enabled.	Direct line-of-sight communication between the source and receiver is required. Performance may be affected by ambient light conditions. Dependency on the availability and proper functioning of light sources exists.

3.5 Challenges of IPS in Warehouse Environment

Though some intelligent systems in warehouse environments that utilize IPS have transitioned from experimental to commercial stages, further analysis and discussion are still needed to address the proposed research questions and reveal the challenges of IPS application in warehouse settings.

3.5.1 Complexity of environment

The indoor warehouse environment is characterized by its dynamic and complex layout, including obstacles, fluctuating light conditions, and electronic interference [50]. Various interference sources typically plague indoor environments, such as illuminance affecting optical sensors and temperature and sound affecting ultrasonic sensors [133]. Furthermore, the density of shelf space can compromise the wireless and optical signals, affecting positioning accuracy [78] [134]. These complexities contribute to the unique challenges when implementing indoor positioning technologies in warehouse environments.

3.5.2 Unknown environment

Current positioning technologies often rely on prior environmental information, as is the case with Wi-Fi [14], [135] [136], UWB [84], and RFID [137], [138]. Pre-set beacons or signal base stations are commonly used in these technologies [33]. However, obtaining such environmental information in real-world warehouse settings can be challenging, as can mitigating interference with wireless base stations or accounting for randomly changing layouts. Therefore, the realization of environment-independent positioning technology remains a challenge.

3.5.3 Balancing IPS accuracy and cost

Economic efficiency serves as a key consideration in commercial applications [24]. Higher IPS accuracy often comes with a higher price tag [25], necessitating the development of low-cost, high-accuracy solutions. The focus has thus shifted to balancing cost and accuracy to facilitate the broader adoption of IPS technology.

3.5.4 Multi-technology integration

Due to varying positioning principles and methods, different technologies are employed for indoor positioning, each with its impact on indoor applications. Various factors such as accuracy, cost, and deployment difficulty often necessitate combining multiple technologies. For example, Kwon et al. [25] utilized a blend of images, LiDAR, and IMU information to obtain UAV attitude information for warehouse inventory applications. Challenges such as inconsistent signal measurement units, sampling frequencies, and accuracy restrict the growth prospects of IPS technology.

3.5.5 Limited computing resources on mobile terminals

The involvement of mobile terminals in IPS is crucial, and hardware limitations can restrict the operational lifespan and the capability to run complex positioning algorithms [24]. For instance, achieving high-speed positioning requires substantial onboard UAV computing power, which demands more energy supplies. This limitation hampers the broader use of IPS.

4. CONCLUSIONS

In the context of Industry 4.0, a growing need for intelligent warehouse management solutions is observed, and attention is increasingly directed towards IPS as the foundational technology for automating and informatizing the warehousing and logistics industry. The Scoping Review method was followed in this study, guided by the PRISMA checklist, to identify and synthesize existing literature on IPS applications in warehouse environments from databases within WOS, IEEE, and SCOPUS. Comprehensive survey and research results are provided in three aspects: (1) the current state of IPS adoption in warehouse environments; (2) the technologies utilized for IPS adoption in these environments; and (3) a framework for evaluating IPS in warehouse settings. Challenges identified in this scoping review for the holistic application of IPS in warehouse environments, particularly inventory management.

Research Question 1 (RQ1) analysis found that IPS primarily focuses on inventory and logistics management tasks in warehouse environments. These applications aim to upgrade existing warehouse operations to enhance efficiency and minimize manual labor. Additionally, multiple studies aimed at integrating IPS with efforts to digitize warehouses were identified. These kinds of applications, distinct from the previous categories, may serve as foundational steps towards realising Industry 4.0 by enabling comprehensive digitization of warehouse processes. For Research Question 2 (RQ2), a comparative analysis of IPS technologies revealed their respective strengths and limitations in inventory management tasks. RFID is widely recognized for its cost-effectiveness and scalability, making it ideal for bulk inventory tracking and routine stocktaking. UWB excels in high-precision dynamic inventory tracking in large or multi-level warehouses, while LiDAR offers advanced 3D mapping capabilities for static or semi-static inventory spaces. Wi-Fi provides a cost-sensitive option for smaller warehouses with simpler layouts. The findings underscore the importance of selecting IPS technologies based on the specific requirements of inventory management tasks, such as applicability, accuracy, cost, energy efficiency and scalability. Regarding Research Question 3 (RQ3), the study proposed a framework for evaluating IPS technologies in inventory management, incorporating quantitative and qualitative criteria. Quantitative metrics, such as accuracy and real-time capability, can be directly obtained from existing studies, while qualitative criteria, such as scalability and adaptability, require interpretative analyses. The framework emphasizes the need for task-specific evaluation to address the diverse concerns of inventory management in dynamic warehouse environments.

Future research explores integrating IPS technologies with emerging advancements in artificial intelligence and deep learning. For instance, combining IPS data with deep learning algorithms can enhance localization accuracy and predictive capabilities in dynamic warehouse environments. Additionally, developing hybrid IPS solutions, leveraging the complementary strengths of technologies such as UWB and LiDAR presents a promising avenue for addressing the trade-offs between precision, scalability, and cost. Finally, applying IPS in complex, multi-modal logistics systems and highly automated warehouses offers significant innovation potential, paving the way for realizing Industry 4.0.

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CONFLICT OF INTEREST

The authors declare no conflicts of interest, either financial or non-financial, including political, personal, or professional relationships that could have influenced the manuscript.

AUTHORS CONTRIBUTION

Xiaodong Zhang (Writing – original draft; Conceptualization; Methodology; Validation; Formal analysis; Data curation; Visualization)

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AVAILABILITY OF DATA AND MATERIALS

The data supporting this study’s findings are available on request from the corresponding author.

ETHICS STATEMENT

Not applicable

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