logistics

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Review

Indoor Positioning Systems in Logistics: A Review

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Abstract: *Background:* Indoor Positioning Systems (IPS) have gained increasing relevance in logistics, offering solutions for safety enhancement, intralogistics management, and material flow control across various environments such as industrial facilities, offices, hospitals, and supermarkets. This study aims to evaluate IPS technologies' performance and applicability to guide practitioners in selecting systems suited to specific contexts. *Methods*: The study systematically reviews key IPS technologies, positioning methods, data types, filtering methods, and hybrid technologies, alongside real-world examples of IPS applications in various testing environments. *Results:* Our findings reveal that radio-based technologies, such as Radio Frequency Identification (RFID), Ultra-wideband (UWB), Wi-Fi, and Bluetooth (BLE), are the most commonly used, with UWB offering the highest accuracy in industrial settings. Geometric methods, particularly multilateration, proved to be the most effective for positioning and are supported by advanced filtering techniques like the Extended Kalman Filter and machine learning models such as Convolutional Neural Networks. Overall, hybrid approaches that integrate multiple technologies demonstrated enhanced accuracy and reliability, effectively mitigating environmental interferences and signal attenuation. *Conclusions:* The study provides valuable insights for logistics practitioners, emphasizing the importance of selecting IPS technologies suited to specific operational contexts, where precision and reliability are critical to operational success.

Keywords: logistics; indoor positioning system; tracking; indoor technologies

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1. Introduction

Geolocation systems track the position of tags; however, while GPS is effective outdoors, it faces limitations indoors due to interference. Indoor positioning systems (IPS) are therefore essential in various environments and applications, particularly in the context of ongoing digital transformation [1]. These systems have gained increasing importance due to their capacity to provide precise location data, thus enabling a wide range of applications across different industries. The growing interest in IPS stems from their potential to deliver substantial benefits and support diverse use cases. For example, in industrial intralogistics, IPS can be used to track goods [2,3] and operators [4–6], enabling companies to make informed decision-making based on real-time data. For instance, by visualizing flows, businesses can optimize their operations, identify bottlenecks, and improve overall efficiency [7]. Moreover, the location data obtained from these systems can be used to define optimal routes [8], ensuring timely and cost-effective intralogistics operations.

Automated Guided Vehicles (AGVs) are another area where geolocation systems play a crucial role. By providing precise location data, IPS can facilitate the seamless operation of AGVs, ensuring they navigate efficiently through warehouses or production facilities [9–11]. This not only improves productivity but also reduces the likelihood of collisions and other operational disruptions. In addition, IPS can help identify and prevent incidents by monitoring the movement and location of personnel and equipment, thereby enhancing safety and reducing the risk of accidents [12–14].

Similarly, geolocation systems can significantly enhance warehouse management by streamlining the orderly picking of goods [15–19]. By tracking the location of items and workers, IPS can streamline the picking process, ensuring that the right items are picked in the most efficient order. This reduces errors, speeds up order fulfillment, and enhances overall customer satisfaction.

Moreover, there are human services that have not been tested in industrial settings but still have goals relating to accuracy testing, safety, intralogistics design and management, and material flow control. For instance, In [20], the authors conducted a study on the geolocation of elderly individuals in a nursing home to ensure their safety. Additionally, in reference [21], the authors used an indoor geolocation system to navigate a micro aerial vehicle (MAV) for stock management at an office site, while the reference [22] planned the routes of a robot after geolocalizing it in a laboratory. In [23], the authors investigated the use of a tracking system in a classroom. In [24], the authors geolocalized individuals in a shopping mall to provide them with advertisements for their safety during COVID-19.

The precision of these systems must be considered as many applications demand high accuracy. For instance, a robot may need to halt at a specific point to pick up items in a warehouse [9]. IPS utilize various technologies to pinpoint the location of objects or people within indoor environments [25]. Some of the primary IPS include radio-based technologies like Wi-Fi, Bluetooth (BLE), UWB, and RFID, as well as light-based, sound-based, magnetic-based, and inertial-based technologies. These technologies utilize advanced methods for position calculation, including multilateration, proximity-based techniques, and fingerprinting. They also apply filters such as particle filtering, Kalman filtering, and Convolutional Neural Networks. Additionally, data integration techniques are employed to address the challenges of indoor positioning, offering tailored solutions for specific needs and environments. It follows that each technology has unique advantages and limitations, making them suitable for different applications and environments in logistics.

1.1. Motivation for This Study

Given the wide range of applications in logistics, we aim to provide a review that can guide practitioners in evaluating different combinations of IPS and their performances in different environments.

Our study examines 104 papers to understand the characteristics of indoor positioning systems in environments such as industrial settings [5], offices [21], supermarkets [26], and hospitals ([20]). These environments were used to conduct experiments with indoor positioning technology and pose various challenges due to interferences such as metallic obstacles [27,28], physical obstacles such as people [29], or magnetic interferences [5], leading to Non-Line of Sight (NLOS) conditions [7], reflections [30], and multipath effects [31] that affect accuracy. To address the challenges posed by these interferences and to achieve better accuracy, our literature review discusses various technologies and methods, focusing on papers relevant to logistics applications.

Table 1 shows a comparative overview of previous literature reviews on IPS with a specific focus on logistics applications. Key aspects compared include consideration of the environment, technologies, data, filters, and methods considered in our paper.

Table 1. Literature reviews.

Title	Year	Environment	Technologies	Data	Filters	Methods
[32]	2020	No	No	No	Yes	No
[33]	2022	No	Yes	Yes	No	No
[34]	2022	No	Yes	Yes	No	Yes
[35]	2023	No	Yes	No	Yes	Yes
[36]	2023	No	Yes	Yes	No	Yes
Our paper	2024	Yes	Yes	Yes	Yes	Yes

In [32], Rácz-Szabó et al. provided a comprehensive overview of indoor positioning technology applications in production, logistics, quality monitoring, and safety. Their article focuses on how these applications interact with the manufacturing execution system (MES) and production within a company, but it does not delve into the technology, data, or methods in depth as deeply as our literature review. While they explained machine learning techniques, we also demonstrated the use of data preprocessing filters alongside these techniques.

Similarly, in [33], Tyagi et al. focused on the implementation of radio-based technologies and mentioned hybrid technologies to enhance robot navigation accuracy. However, our article includes a broader range of position calculation technologies, methods, and filters. While, in [33], the authors explained data and distance-based methods, their research did not cover the filters and methods that improve tag position accuracy.

With a more general framing in [34], a literature review has been conducted on commonly used technologies, algorithms, and techniques, highlighting their advantages and disadvantages. In contrast, our research emphasizes logistics issues, the environments where these technologies are applied, and the available filters and their applications, which were not addressed in [34].

A specific literature review on industrial applications involving MAV was presented in [35], covering topics such as safety and MAV charging. This review focused exclusively on UAVs, whereas our article includes various tagged entities in motion, such as people, vehicles, UAVs, AGVs, and items. Additionally, in [35], Awasthi et al. do not address data used for position calculation.

Lastly, in [36], Sartayeva et al. conducted a literature review that inspired our study. Building on [36], we delve further into hybrid technologies, which are adapted to various environments to address interference issues, providing numerous examples demonstrating high accuracy.

In conclusion, the comparative analysis in Table 1 underscores gaps in existing reviews, such as the limited exploration of how environmental factors, technology combinations, and data integration affect system accuracy and reliability in logistics. Our review makes a unique contribution by focusing on the environmental conditions in which technologies were tested, highlighting the impact of obstructions on system performance—an often overlooked factor in previous reviews. Unlike in work by other researchers, we provide specific accuracy values (in cm) for the best combinations of data, technologies, filters, and methods. Our study fills these gaps by offering a detailed analysis of the methodologies used in indoor positioning systems. By addressing these key aspects, we contribute to a deeper understanding of indoor positioning technologies and offer guidance for optimizing their use in complex logistics environments, thus improving both accuracy and operational efficiency.

1.2. Aims of This Study

To understand the existing and most used IPSs in the literature, their common applications and scopes in logistics, their accuracy, and their effectiveness in different environments, we formulated the following research questions (RQ), which guided our work:

RQ1: Which IPSs exist in the literature?
RQ2: Which IPSs are most commonly used in logistics, depending on the environment in which they are tested?
RQ3: What are the aims of reviewed contributions?
RQ4: What IPS pairings were utilized?
RQ5: What level of accuracy does a specific IPS achieve depending on the environment in which it is used?

The explanations for the research questions (RQs) are divided into several sections. The answer to RQ1 is provided in Sections 3.5–3.9, as these sections covered different IPS utilizing diverse technologies, methods, filters, communication protocols, and data. Similarly, the answer to RQ2 can be found in Sections 3.5–3.9, as these sections cover various IPS that use diverse technologies, methods, filters, communication processes, and data used in different environments. For RQ3, the answer is located in Sections 3.3 and 3.4, which discuss the four types of aims of contributions for tracking various actors. RQ4 is addressed in Section 4, highlighting how different combinations of technologies, methods, and filters are used. Finally, the answer to RQ5 can be found in Sections 3.2 and 4, where we explain how IPSs are influenced by the environmental geometry and the combinations of different technologies applied.

2. Materials and Methods

2.1. Material Collection and Selection

The search was conducted using Scopus on 24 August 2024. After developing the research questions, we applied several criteria to select relevant papers during the initial review. The inclusion criteria were papers written in English that focused on logistics applications, utilized IPS and were published after 2010 in journals categorized as research or review articles. When searching, the query was configured to look for the words in Table 2 within the titles, abstracts, or keywords of the papers in Scopus. This table consists of 3 columns: Group A, Group B, and Group C. Each selected paper had to include at least one keyword from each group.

Table 2. Query on Scopus.

Group A		Group B		Group C
indoor positioning system		indoor technique		logistic
or		or		or
indoor positioning	AND	indoor technologies	AND	supply chain
or		or		or
indoor system localization		indoor solution		warehouse

The exclusion criteria were as follows: proceedings, book chapters, editorials, and reviews. Figure 1 illustrates the methodology of the systematic literature review, which was divided into three phases: identification, screening, and inclusion. In the identification phase, research questions were formulated, relevant keywords were selected, and inclusion criteria were established. This search resulted in 338 pertinent records. In the screening phase, records were filtered based on exclusion criteria, which eliminated 214 proceedings and 11 reviews. The abstracts of the remaining 113 records were then assessed to determine their relevance. In the final phase, inclusion, 104 full-text articles were assessed based on their full text. This systematic approach ensured that only the most relevant and high-quality studies were included in the literature review, allowing for a comprehensive analysis of indoor positioning systems and their applications.

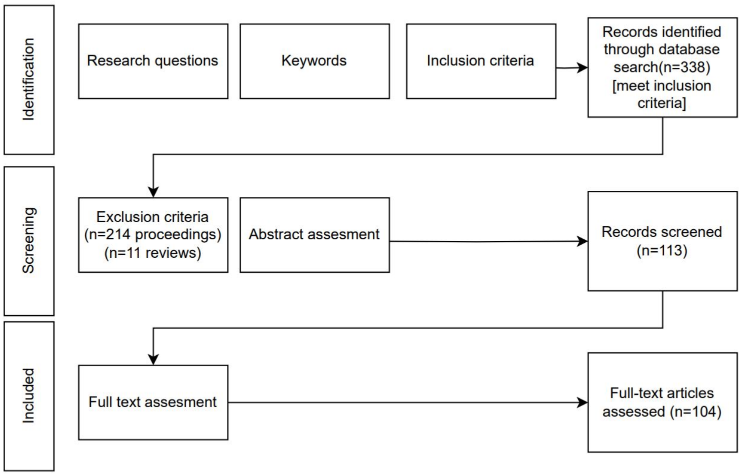

Figure 1. Selection process diagram.

2.2. Material Analysis

Table 3 presents a framework for the descriptive and logistical analysis of the reviewed papers on indoor positioning systems with applications in logistics. It categorizes the data into several key sections, enabling a structured and thorough evaluation of each study. The categories include the following:

- Year, country, subject area: these columns capture the basic bibliometric information of the papers, providing insight into the temporal and geographical distribution of the research.
- Test environment, actor, aims of contributions: these columns detail the context in which the IPS is deployed, including the type of environment (e.g., industrial setting and hospitals), the specific actors being tracked (e.g., personnel and assets), and the area of aims for contributions area (e.g., material flow control and safety).
- Communication, technology, and combinations: these sections identify the communication technologies and specific IPS technologies used, as well as any combinations of these technologies, indicating the complexity and integration of different systems.
- Data, methods, hybrid technologies: these columns describe the types of data collected, the methods used for position calculation, and any combinations of methods, highlighting the diversity in data processing and analytical approaches.
- Filters, parameters, machine learning: this part focuses on the filtering techniques applied to improve accuracy, including traditional parametric filters and advanced machine learning-based algorithms.
- Accuracy: this column captures the level of accuracy achieved by each IPS in different environments, which is crucial for evaluating the performance and reliability of the systems.
- Technology accuracy analysis: this section illustrates examples of both the best and worst accuracy results, while explaining how these results are achieved by utilizing all the previously discussed characteristics.

The general analysis aims to classify the selected papers to understand the level of interest in the topic of IPS for logistical aims. This analysis of logistics is relevant to understand how IPS works in terms of technology, data, methods, and filters to track actors in different environments. This understanding can help practitioners apply IPS in logistics effectively.

Overall, the table serves as a detailed matrix for categorizing and analyzing the various aspects of IPS research, providing a clear and organized overview of the factors influencing the effectiveness of these systems in different logistical contexts. Most of the analyses are conducted for each type of environment. However, in a few cases, it was deemed unnecessary, and for these cases, the diagrams are titled “Total”.

Table 3. Categories for the analysis.

Category	Sub-Category
General Analysis	
Descriptive Analysis	Year Country Subject area
Logistics Analysis	
Test environments	Industrial setting Office Hospital Supermarket
Actors	Person Item Robot Manual vehicle MAV UAV AGV
Aims of contributions	Material flow control Intralogistics design and management Safety Accuracy test
Communication layers	Light-based Radio-based Sound-based
Technologies	Acoustic Bluetooth LORA RFID Ultrasound Visible light Wi-Fi Zigbee
Datas	Signal characteristic-based Angle-based Time-based Image-based
Methods	Computer-based Constraint-based Fingerprinting Geometric Proximity-based
Filters	Parametric-based Machine learning-based

3. Results

3.1. Descriptive Analysis

The descriptive analysis includes various statistics on the 104 papers included in this research. The columns "Year", "Country", and "Subject Area", describe the following aspects of the reviewed papers:

- Year: indicates the publication year of each paper, providing a temporal context for the research.
- Country: specifies the country of the authors' origin, giving a geographical context.

- Subject Area: identifies the academic or research field to which the study belongs, highlighting the disciplinary focus.

In Figure 2, we can see the number of published documents from 2011 to 2024. The graph reveals a period of low publication activity initially, followed by a gradual increase starting around 2018 and culminating in a peak in 2022 with the highest number of documents published, reaching 21. The dotted line represents an exponential growth trend, indicating that the number of published documents tends to accelerate over the years. The data were fitted using an exponential formula: y = a $\times$ $e^{b\times x}$, where the parameter a is 4×10^{-142} and b is 0.1622.

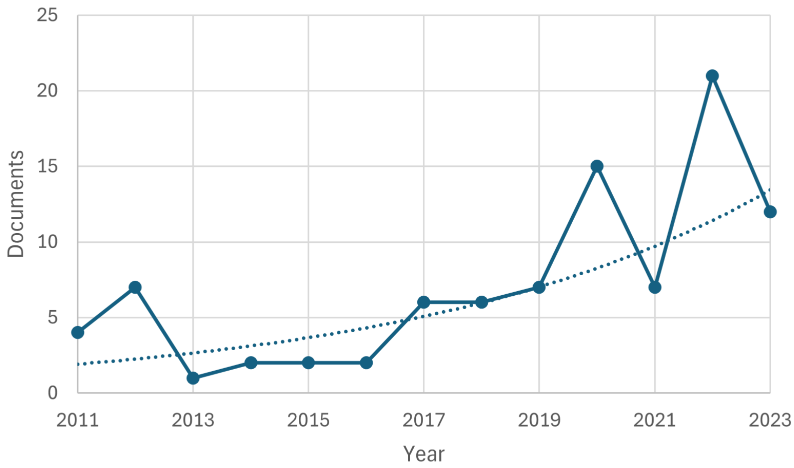

Figure 2. Number of annual published articles between 2011 and 2024.

The spatial distribution is shown in Figure 3. China is the primary country of publications, based on the author's origin, followed by Italy. Hong Kong also shows significant interest in this topic. Given the number of manufacturing companies in China, tracking materials [37–39], AGVs [22,40,41], and people [4,42,43] are indispensable for efficient production.

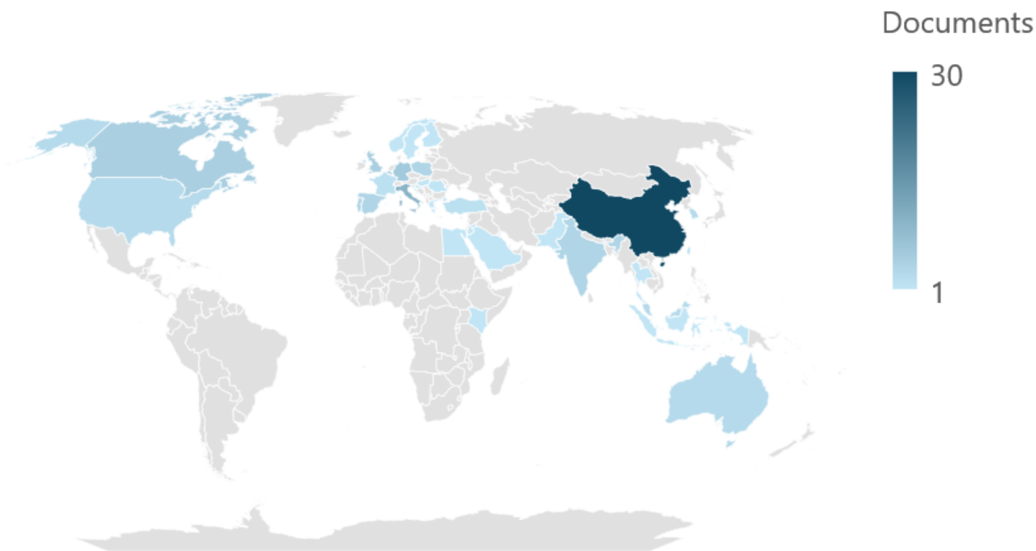

Figure 3. Top ten countries.

Figure 4 shows the distribution of subject areas. The subject areas most involved in this topic are engineering ([44–46]) and computer science ([47–49]) as several applications are relevant to these fields.

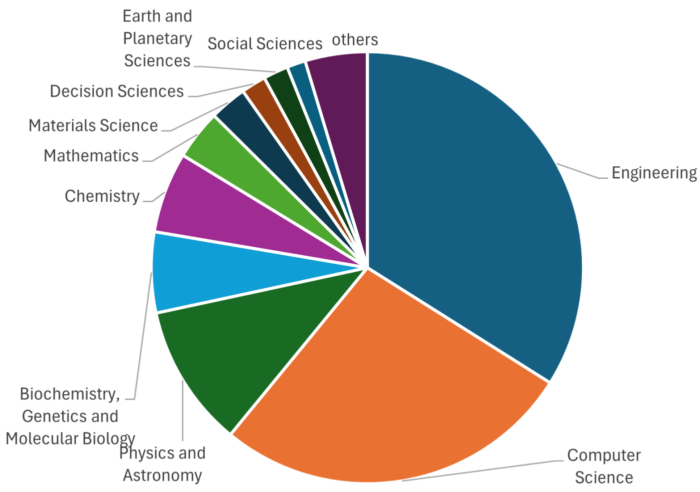

Figure 4. Specific subject area grouping.

3.2. Test Environments

3.2.1. Environmental Disturbances

We added an environmental layer to account for different test locations, as varying environments can impact the accuracy of indoor positioning systems (IPS) due to their distinct shapes and potential interferences. For example, a warehouse may experience more signal interferences, such as obstructions and multipath, compared to an office on a campus. Additionally, signals in a warehouse may face interference from magnetic fields created by other technologies in the production environment. The impact of these interferences has been demonstrated by [50], which utilized an IPS that was validated in the operational industrial environment of the Centro Bahía de Cádiz Airbus factory. This complex indoor setting includes metallic structures and working personnel, which caused significant interference. Similarly, the reference [51] examined the performance degradation of a UWB system under full occlusion, using timber and steel as blocking materials. Under controlled laboratory conditions, the average error was approximately 8.9 cm. However, in a real-world construction site, errors ranged from 40 cm to 120 cm, depending on congestion and the line-of-sight visibility between the tags and receivers. Additionally, in [45], the authors reported that accuracy depends on the test scenario, finding that the average localization error ranges from 24 cm to over 1 m, influenced by environmental conditions. Lastly, in [40], the authors demonstrated that localization accuracy depends on various factors like bandwidth and wall material.

3.2.2. Types of Environments

There is a need to categorize the environments where IPS tests were conducted to assess the different levels of accuracy obtained based on the specific environment. For this purpose, we considered four main categories: offices, industrial settings, supermarkets, and hospitals. The first category includes all tests conducted in offices, rooms, or university laboratories. The second category pertains to all industrial environments, such as warehouses, production lines, or shop floors. The last two categories include supermarkets, where museums and libraries were also grouped, and hospitals. For instance, in supermarkets [26], the goal is to send advertisements to the person approaching a shelf. Similarly, in museums [52], information is provided about the piece of art. Determining the exact position of a tag on a library shelf is comparable to locating it on a supermarket shelf, which is why they are grouped under the same environment category [53].

3.2.3. Statistics on the Tested Environments

As shown in Figure 5, the majority of the collected papers investigated IPS in offices [31,54–57], specifically in university offices. Secondly, industrial settings are another type of environment frequently tested [5,38,42,58], as the principal logistics activities take place in these locations. On the other hand, fewer papers conducted tests in supermarkets [26,59] or hospitals [20]. Currently, most testing is carried out in offices or university laboratories, which are ideal locations because they have fewer sources of interference. However, this convenience means that other environments, such as industrial settings, hospitals, museums, libraries, and supermarkets, have not been as thoroughly tested. For example, more studies should be conducted in hospitals to track inventory for better management of medications, streamline queues in hallways, and locate patients with mobility issues, such as those suffering from Alzheimer's or other diseases, as discussed by [20,36]. To achieve more reliable and applicable results, IPS must be further tested in real-world contexts, where conditions are more variable and representative of everyday operational challenges. Thus, future studies should be conducted in real environments.

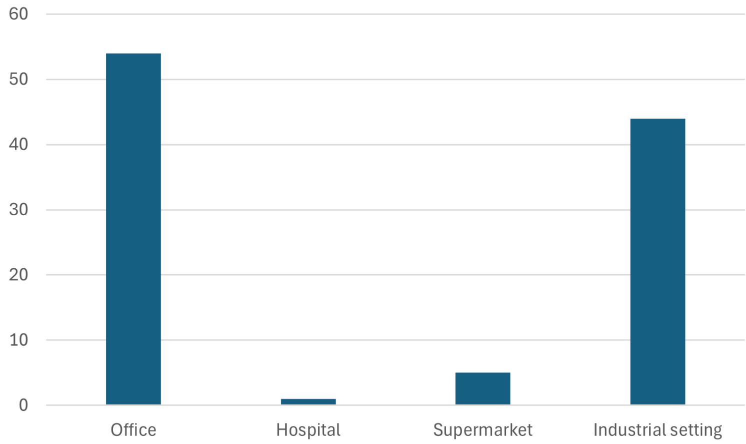

Figure 5. Distribution of papers across different environments.

3.3. Actors

Figure 6 is a pie chart representing the percentage of papers that track each type of actor, such as AGVs [40,60–62], items [63–65]), MAVs ([21,41], unmanned aerial vehicles (UAV) [66–68], UAS, people [59,69,70], robots [22,71,72], or manual vehicles [73–75], such as forklifts or shopping carts. The chart indicates that "Item" is the most tracked actor, followed by "Person".

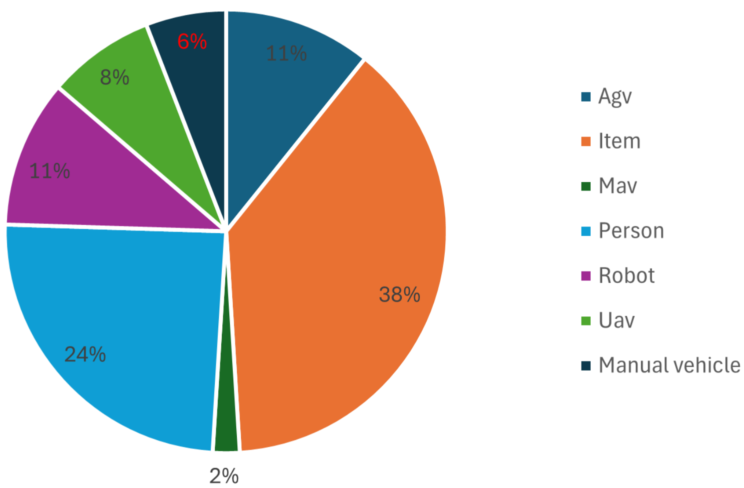

Figure 6. Distribution of tracked actors in indoor positioning systems.

3.4. Aims of Contributions

Indoor positioning systems (IPS) have diverse aims of use, and there is a need to categorize them. For this purpose, we propose a classification based on four main scopes: enhancing safety, optimizing or designing intralogistics, controlling the flow of goods, or testing the accuracy of newly proposed technologies. Thus, as visible in Figure 7, the resulting categories are named: Safety, Intralogistics Design and Management, Material Flow Control, and Accuracy Testing.

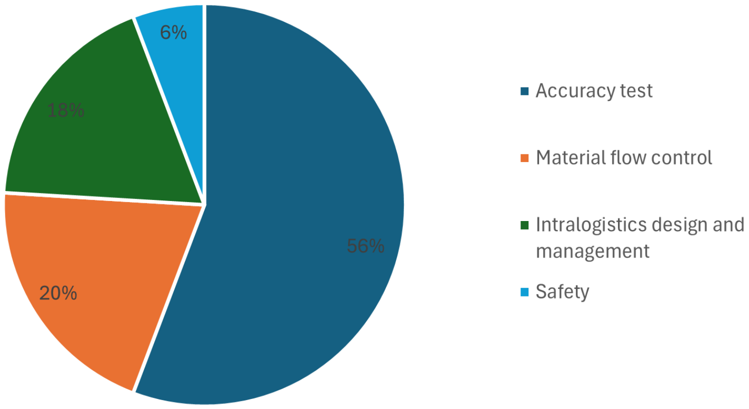

Figure 7. Percentage of contribution aims in indoor positioning.

3.4.1. Safety

The Safety category encompasses all activities related to ensuring the safety of individuals (e.g., elderly people and workers) and vehicles. This category includes applications such as accident detection and the promotion of preventive measures through IPS. For example, in [69], the authors developed an IPS-based system to geolocate people during building evacuations to ensure that each occupant leaves the building. In the safety category for industrial environments, we found studies ensuring worker safety in cold warehouses. For instance, in [12], the authors created an indoor safety tracking system that detects motionless behavior to identify abnormal conditions in a cold warehouse. Similarly, in [39], worker safety was monitored based on their movements in a cold storage warehouse. IPS systems have been employed not only in industrial environments but also in hospitals, as seen in [20], where elderly patients were equipped with tag bracelets worn on their wrists. These wristbands contained active RFID tags, which enabled real-time monitoring of their body temperature, location, and overall condition. These data are essential for the hospital's information system, helping reduce the likelihood of accidents.

3.4.2. Intralogistics Design and Management

The second category pertains to IPS applications that aim to enhance the design and management of intralogistics, including optimizing internal transportation, route planning, and picking processes. For example, in [8], the authors mapped AGVs with IPS so that they could collaborate, share resources, and optimize their routes. Regarding route optimization, in [76], the authors defined the default route for multiple order pickers to mitigate congestion in real time, which is based on IPS and information sharing. Similarly, in [55], the authors used IPS to locate AGVs and optimize their routes, while in [10], IPS was used not only to allow AGVs to navigate a warehouse and choose the optimal route but also to map the space where they move. Route optimization and autonomous navigation based on IPS were also applied for UAVs [77]. In this same category, we found works that attempt to optimize robot movements, as seen in [22,78]. Lastly, related to intralogistics optimization, we found applications that optimized layout design, as seen in [79], where IPS was exploited to identify bottlenecks and backlogs, helping to redesign the facility layout.

3.4.3. Material Flow Control

The third category encompasses all the applications related to controlling the flow of goods. These include inventory tracking, monitoring work in progress, and providing real-time status updates on stored items. Examples from this category that aimed to control items in production processes include the study by [80], where IPS was used to deliver light parts by UAV to workstations within a manufacturing plant. Similarly, in [17], the authors utilized radio frequency technology for monitoring labeled items moving on a conveyor belt to determine their order of arrival. Along the same lines, in [79], the authors aimed to enhance production by tracking the items involved in the process, while in [51], the authors monitored construction progress and materials on a construction site in real time. Regarding inventory management, in [66], the authors flew a drone into a warehouse to scan the inventory, while in [37], the authors exploited IPS in a cotton bale storage warehouse to track their location and monitor their characteristics (e.g., humidity and temperature). Another application relevant to inventory management was developed in [50], where IPS was used to guide UAVs to search for lost items in a warehouse. Lastly, other applications in this category focused on effectively managing order picking. For example, in [15], the authors supervised order-picker movements and the movement of items between workstations in a manually operated warehouse, while in [16], the authors focused on reducing the overall time required for order-taking with the help of IPS, which, in turn, enhances effective stock management.

3.4.4. Accuracy Testing

The purpose of the last category of contributions reviewed identified is to test the accuracy of IPS applied to track objects or people. This category includes, for example, the study by [7], where the authors tested the accuracy of a UWB system in reconstructing the routes of small electrically guided vehicles. The accuracy of UWB was also investigated in [70], where the authors utilized an IPS to geolocate individuals. Other studies in this category evaluated IPS based on RFID, as seen in [26], where RFID accuracy was tested in a supermarket; in [43], where RFID accuracy was evaluated concerning multi-target tracking in logistics; and in [81], where the authors aimed to monitor the movement of an object within a 3×3 square meter office on campus. Another study in this category evaluated the accuracy of a new infrared (IR) optical system intended for low-cost and simple indoor coordinate measurements of large objects [82]. In this category, we also found works that tested the combination of different technologies, as seen in [83], where an IPS based on Wi-Fi and LORA was tested to assess its accuracy and the impacts of interferences. The combination of UWB and IMUs (inertial measurement unit) was evaluated in [84] to track a quadcopter, and the combination of IMUs and visible light was evaluated in [42] to follow a robot in a warehouse. As visible in Figure 7, the majority of contributions (56%) involved testing IPS systems. This highlights the crucial need to assess the accuracy of IPS systems before real-world applications in logistics. Real applications comprise the remaining 44% of the collected papers, which are divided between 20% related to Material Flow Control, 18% to Intralogistics Design and Management, and lastly, 6% to Safety. From this analysis, we can conclude that future research must focus on the already developed and tested IPS applications to understand their impacts on logistics, with a focus on safety, which is the least investigated area.

3.5. Communication Layers

Figure 8 depicts five pie charts, each representing the distribution of communication layers used in the different logistical environments identified. We identified three types of communication layers: light-based [85], radio frequency-based [68], and sound-based [86].

In general, radio frequency-based communication is the most commonly used method across all environments. In supermarket and hospital environments, only radio-based systems were employed. In [56], the authors used passive UHF-RFID to improve the navigation system of an AGV in a campus room. In [38], the authors used BLE and UWB to track items in a world-leading computer manufacturer's factory. Similarly, [31] tracked items and people with Wi-Fi on campus; it gave low accuracy, showing ample range for improvement. In [21], the authors used LORA technology to let a MAV navigate in both the warehouse and outdoor environments, this technology uses the signal that has to pass through walls. However, the data are taken at a low frequency to use little battery power, resulting in positioning accuracy in meters and not centimeters. In [28], the authors utilized Zigbee radio-based technology to track assets within a room but encountered interferences and multipath issues.

Light and sound-based communications are only minimally utilized in specific contexts such as industrial settings and offices. For instance, a light-based communication system was used by [87]. In [11], the authors aimed to geolocalise the robot using infrared technology. In another example, [71] used visible light-based technology, employing LEDs and a camera to track a robot in a warehouse.

Sound-based systems were not used in industrial settings but appeared exclusively in offices. In [88], the authors utilized ultrasound technology to track items in a real-world experiment in a warehouse-like scenario. In [86], the authors used an acoustic sound-based system and support vector machine SVM method to classify LOS and NLOS with the connected classification accuracy.

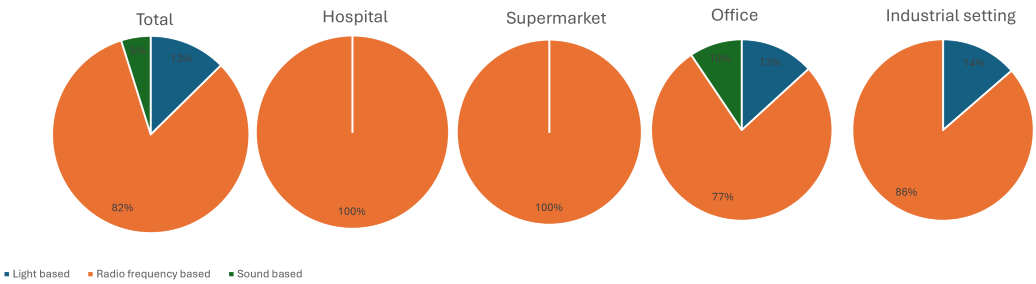

Figure 8. Preferred communication types for indoor positioning by environment.

3.6. Technologies

Figure 9 consists of four bar charts depicting the number of papers on various communication technologies across different environments: total, hospital, supermarket, office, and industrial settings. The "Total" category represents the combined values from the other environments. Sound-based technologies include acoustic and ultrasound, while light-based technologies include infrared and VLC (Visible Light Communication), with the remaining being radio-based, including BLE, LORA, Wi-Fi [89], RFID, UWB, and Zigbee [90]. Ultraviolet light is not used due to potential health risks associated with prolonged exposure.

RFID technology is the most widely used overall [81,91] as stated by [92], followed by UWB, particularly in hospital and industrial environments, respectively. This technology can be categorized as active or passive RFID. The main distinction between passive and active RFID lies in how RFID tags (transponders) are powered and their operational functionality. Passive RFID tags do not have an internal power source, while active ones usually use batteries. It is technically possible to use passive RFID for a limited form of real-time positioning. However, limitations in reading distance, update frequency, accuracy, and interference make this approach less effective compared to using active RFID. Active RFID, with its ability to transmit data over long distances and provide more frequent updates, is generally preferred for real-time positioning applications that require high precision and reliability. Passive RFIDs are commonly used in applications such as access control systems, inventory management, electronic passports, and contactless payments, while active RFIDs are used in applications that require long-distance reading or active tracking, such as vehicle tracking, real-time asset tracking, and ensuring worker safety in hazardous environments. By integrating passive RFID with other technologies, such as Wi-Fi, BLE, or UWB, these limitations can be overcome, thereby enabling effective real-time tracking.

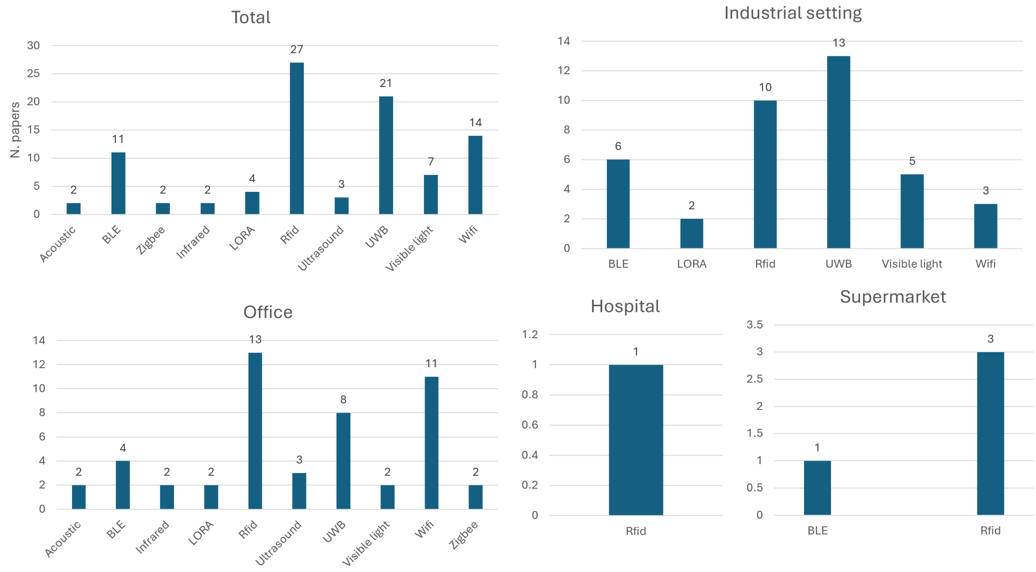

Figure 9. Indoor positioning technologies.

The UWB system is the most used technology in industrial settings because it can distinguish between direct and reflected signals thanks to its fine temporal resolution capability [2]. However, as noted by [13], time synchronization and accurate positioning of anchors are critical to maintaining UWB tracking system accuracy. Properly managing these aspects is crucial, as neglecting them can adversely affect the performance of the real-time tracking system.

Wi-Fi is the third most used technology, especially used on campuses [40,41,89,93]. In particular, Li-Fi, along with Wi-Fi technology, minimizes electromagnetic interference, making it ideal for sensitive environments like medical or industrial settings while providing faster connection speeds than traditional radio-based technologies.

BLE is also a notable technology across different environments, while acoustic and Zigbee receive minimal attention.

Overall, more technologies were tested on campus than in other environments, including ZigBee, ultrasound, LORA, and acoustic.

In our study, we found that these technologies can be used in combination with each other or with magnetic and inertial technologies. We observed that magnetic and inertial technologies were applied only in combination with radio-based, light-based, or sound-based technologies in the papers we analyzed. The combinations of technologies will be discussed in more detail in the next section.

Hybrid Technologies

A hybrid IPS, or indoor positioning system, employs a combination of technologies (see Table 4) to work together, enhancing the accuracy and reliability of position detection. These systems integrate various methods, such as the following:

1. Radiofrequency (RF) technologies: Wi-Fi, Bluetooth, and RFID.
2. Optical Technologies: machine vision and infrared signals.
3. Ultrasound: high-frequency sound waves to measure distances.
4. Magnetometers: detection of changes in magnetic fields.
5. Motion sensors: accelerometers and gyroscopes.

By combining these technologies, a hybrid system can overcome the limitations of individual methods. For example, RF signals can be blocked by physical obstacles, but motion sensors help maintain high tracking accuracy. A hybrid approach creates a more robust and accurate system that can work effectively in different indoor environments with various features and obstacles. For instance, in [6,9,47,94] the authors utilized an IMU in combination with radio-based technology to improve distance, acceleration, and position calculations. In [95], the authors achieved different levels of accuracy depending on whether they used IMU data. When using IMU, the accuracy was under 1 m, whereas, without the use of inertial systems, the positioning errors remained below 3 m. Ref. [38] used BLE for general tracking due to its high accuracy, low power consumption, low cost, and high scalability. UWB is used to obtain accurate location labels during the offline phase, which serve as training input for supervised learning of the neural network model. RFID is used for simple proximity identification and is easy to implement.

In summary, the combinations involving UWB appear frequently paired with other technologies like BLE in [38], RFID in [73], and IMU in [47]. Wi-Fi is another common technology in these combinations, paired with LoRa in [83], IMU in [9], or in a trio with BLE and RFID in [8].

Table 4. Technologies combinations found in the paper analyzed.

Reference Paper	Technologies	N. Papers
[50]	UWB and VLC	1
[38]	UWB and BLE	2
[73]	UWB and RFID	2
[83]	Wi-Fi and LORA	2
[8]	BLE, Wi-Fi, and RFID	1
[94]	UWB, IMU and BLE	1
[6]	RFID and IMU	1
[9,41]	Wi-Fi and IMU	3
[47,77]	UWB and IMU	3
[62]	LORA and IMU	1
[95]	BLE, Wi-Fi, and IMU	1

The focus on these combinations suggests a research interest in exploring the complementary strengths of these technologies in various applications.

3.7. Data

Numerous types of data are utilized for positioning and communication between tags and anchors. These can be categorized based on signal characteristics, angles, and time. Signal characteristic-based data include received signal strength indicator (RSSI), phase difference of arrival (PDoA), and channel state information (CSI). In [5,39], the authors used RSSI data with IPSs in a warehouse. In [58,96], the authors used PDoA data with other radio frequency technologies.

Angle-based data are represented by the angle of arrival (AoA) and angle of departure (AoD). In [26], the authors used AoA data to reduce the obstruction in a supermarket, although no articles employed used AoD.

Time-based data consist of time of arrival (ToA), time difference of arrival (TDoA), time of flight (ToF), and two-way ranging (TWR). For instance, reference [2] used ToF to calculate the position of an item on campus, measuring the travel time of a signal between two points. In [3], the authors used TDoA by measuring the difference in arrival times of a signal at multiple receivers. In [60], the authors used ToA by measuring the specific arrival time of a signal at a single receiver to determine the distance. These techniques are fundamental to various localization and tracking systems used in many modern applications.

Figure 10 illustrates that signal characteristic-based data are widely employed across all environments, as it is the less expensive method, according to [34]. In hospitals and supermarkets, only angle-based and signal characteristic-based data are prevalent due to the limited number of studies in these settings, as depicted in Figure 5. In contrast, the industrial setting shows a higher usage of time-based data compared to other scenarios.

Moreover, the data can be used in a hybrid approach, for example, in [97] the authors used both RSSI and phase data. Ref. [64] used TDoA and AOA data.

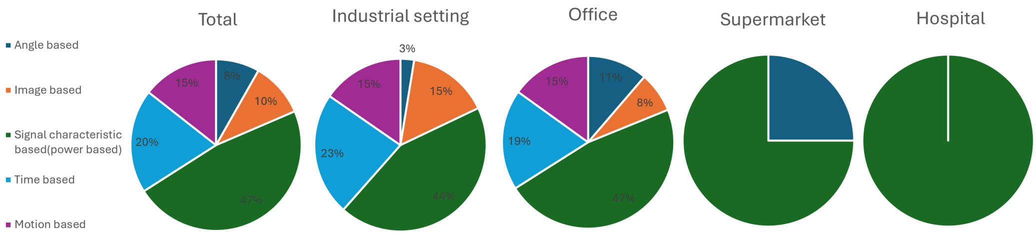

Figure 10. Data.

In addition, various distance-based calculation algorithms can utilize the data to determine the distance between the tag and the anchor ([33,36]). However, converting data into distances is not always necessary; it depends on the method used for calculating the tag's position. Range-based methods involve calculating the distance from the data, while range-free methods do not require this conversion. Nevertheless, distance-based calculations alone are not sufficient for accurately determining the tag's position, so additional methods are often employed.

A Data Comparison

Some data are more precise than others for geolocation purposes. Table 5 presents the papers where one data approach was found to be more efficient than others. In [98], the authors used the RFID system and PDoA data because they are less prone to reflections than TDoA. In [2], the authors utilized UWB technology, ToF data, and a trilateration system, which yielded superior results compared to using RSSI. However, the calculation of positions with ToF is more complex. Nevertheless, ToF measurements can be impacted by multiple reflections and delays. In [69], the authors used RSSI and not AOA or ToF with Bluetooth technology, but the accuracy dropped to 3.5 m. In [99], the authors compared the accuracy results obtained using RSSI and ToF data; the latter produced better results. In [7], the authors combined TDoA and AoA methods to improve accuracy. They also found that TDoA outperforms ToA.

Table 5. Data performance.

Reference Paper	Data That Performs Better	Data That Performs Worse
[98]	PDoA	TDoA
[2]	ToF	RSSI
[69]	AoA ToF	RSSI RSSI
[99]	ToF	RSSI
[7]	TDoA	ToA

Overall, it appears that RSSI is user-friendly but less accurate than other data types.

3.8. Methods

The methods for calculating the position of a tag that must be geolocated are diverse (see Figure 11). In this collection of papers, the following methods have been identified: geometric methods, constraint-based methods, proximity-based methods, fingerprinting, and computer-based methods. For a detailed explanation of these methods, readers can refer to [36]. Geometric methods involve techniques such as multilateration [23] and multi-angulation [100]. The proximity method is an optimization problem focused on finding the point in a given set that is closest (or most similar) to a specified point. Fingerprinting requires an offline phase to train the systems and an online phase to determine the tag's position. Computer-based methods necessitate offline training to create a digital map and computer vision [46]. Other methods include constraint-based approaches, such as belief propagation and maximum likelihood estimation [44,101], semi-definitive programming, and parallel projection method.

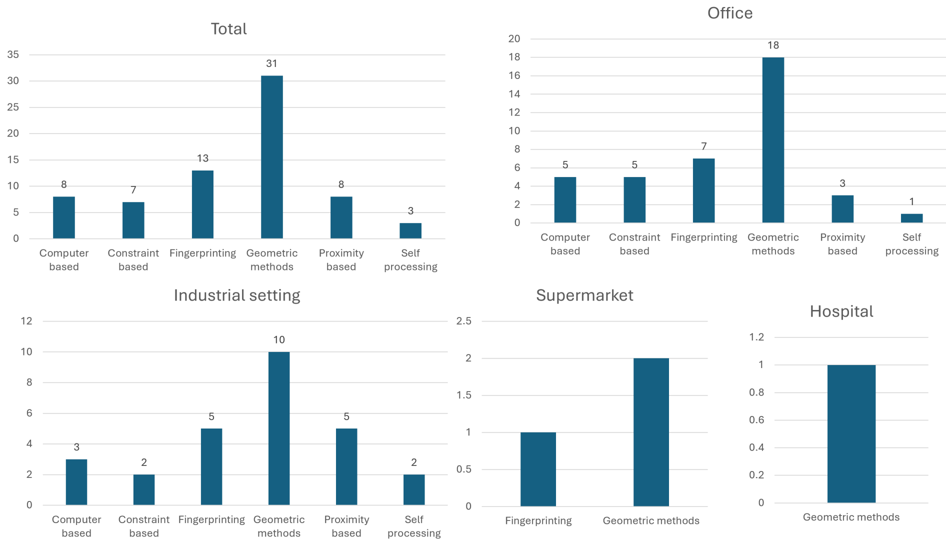

Figure 11. Methods.

Geometric methods are the most studied location methods in these environments; supermarkets and hospitals use only these. Ref. [26] used RFID technology and AOA angle-based data with the multi-angulation method to define the position of the person wearing the reader while the tags are placed on the shelves. In [67], the authors used the method of trilateration with data ToF to use a UAV in a warehouse. The position calculation by [102] used a geometric method of intersecting parabolas to locate the tag. RFID (Radio Frequency Identification) technology by [103] used mobile readers mounted on rails, moving along the x- and y-axes. The position of the continuously scanned tag was defined by intersecting two circles. In [104], the authors used a hyperbolic method with a moving antenna to locate the item in a laboratory, utilizing TDoA data. In [30], the authors utilized the method of intersecting reader radii and adjusting signal attenuation to estimate RSSI. The position error was calculated by comparing estimated and true RSSI values.

In warehouses, proximity methods serve as a secondary option, employing algorithms such as a closest neighbor or centroid localization. In [16], the authors combined the use of proximity, fingerprinting, and trilateration methods. In their study, ref. [71] utilized the iterative closest point method in the first step to create the map. In the second step, they employed the Monte Carlo approach. It is important to note that the robot's geolocation in dynamic environments is more challenging compared to static environments, which could lead to potential changes in its location.

On campuses, fingerprinting is also used as a secondary method. In [27], the authors used fingerprinting with a Wi-Fi system in a room of students of 8×8 m. In [78], the authors used a fingerprinting method to navigate a robot on a campus.

When approaching a particular application or problem, there are often multiple methods that can be employed together to achieve the desired accuracy. By combining different techniques, it is possible to leverage the strengths of each while compensating for their individual limitations. This integrated approach enables more robust and adaptable solutions, providing greater reliability and precision across a range of conditions. For instance, in [12,37] the authors utilized fingerprinting with trilateration, In [5], the authors employed fingerprinting with pedestrian dead reckoning (PDR), while reference [105] used computer-based and geometric methods for signal processing.

3.9. Filters

The filters used for IPSs can be either mathematical or based on machine learning (see Figures 12 and 13). Employing several filters can enhance the accuracy of a system by improving position detection.

The first group included commonly used filters such as the Kalman filter, particle filtering, and moving average. Particle filtering is commonly used in warehouses, while moving average and Kalman filters are preferred in offices. It is worth noting that these filters were not used in supermarkets and hospitals depending on the selected papers. These filters can be applied to preprocess data to calculate the distance between tags and anchors [36]. For instance, in [5], particle filtering was used to correct incorrect measurements of all detected locations of vehicles, using the collected radio signals, due to magnetic perturbations. In [80], the authors used moving averages to improve positioning accuracy and Kalman filters for fusing data from UWB and IMU sensors. The system by [106] employs a Kalman Filter to fuse data from GPS, IPS, and INS (Inertial navigation system), while an Extended Kalman Filter (EKF) is utilized to linearize the non-linear measurement models.

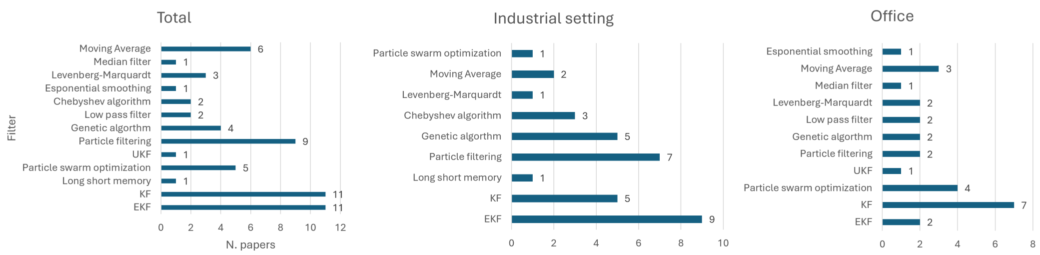

Figure 12. Filters.

The second group discussed various machine learning filters [107], including supervised and unsupervised ones. The collected papers mentioned filters like boosting trees, long short-term memory (LSTM), neural networks (NNs), convolutional neural networks (CNNs), support vector machines (SVMs), random forests, and K-nearest neighbors (KNNs). It indicates that, among all environments, neural networks and convolutional neural networks were the most commonly used. Machine learning filters can be employed for data pre-processing or to define the best estimation position algorithm [32]. For example, the system of [39] used a deep learning unsupervised neural network system to learn to identify accidents in a cold warehouse using distance and vibration data. In [108], the authors used the CNN filtering of input data. In [12], the authors explained that the majority of existing research focuses on reducing errors caused by NLOS and multipath propagation. Bias introduced by UWB and TDOA was addressed using NN and Kalman filters. In [54], the authors enhanced accuracy using deep learning models compared to geometric fingerprinting methods, e.g., predicting initial data.

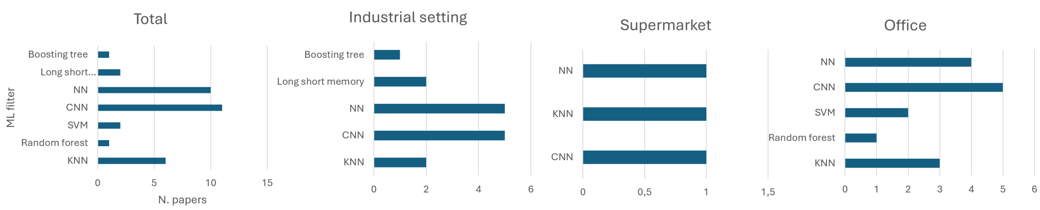

Figure 13. Machine learning filters.

4. Accuracy Analysis

4.1. Accuracy

Indoor positioning systems' accuracy is expressed in various forms in the researched papers, such as distance error, localization accuracy, mean absolute error, and root mean square error. Distance error and localization accuracy measure the difference or precision of the estimated position compared to the actual position as a percentage of occurrence or averaged value across all tests. The mean absolute error is the average absolute difference between the actual and estimated points, while the root mean square error calculates the square root of the average of the squared errors, making it a more complex measure. For all these types of accuracy measurement, a lower value indicates a better result. The accuracy is case-specific; it can vary from 1 cm to 500 cm, as shown in Table 6, based on the indoor positioning technology, the method used for calculating the tag position, the filters applied, and the environment obstructions. The most common accuracy value found among the analyzed papers is 10 cm. In the industrial setting, the accuracy is between 1 and 200 cm, while on campus, it can be as high as 500 cm. The supermarket has a range of 25 to 100 cm, while in the hospital, the accuracy of the positioning system is not defined.

Table 6. Accuracy values.

Test Environment	N. Papers for Range A	Accuracy Range A	N. Papers for Range B	Accuracy Range B	N. Papers for Range C	Accuracy Range C
industrial setting	23	1–99	3	100–200	1	201–500
office	20	1–99	8	100–200	3	201–500
supermarket	2	1–99	1	100–200	0	201–500

Given that the accuracy ranges are quite similar across all environments, with the value of 500 found only once on campuses, it is believed that the quality of the system is not solely determined by the environment. Instead, it also relies on other factors we have covered, such as the data, computational methods, filters, technologies used, and the system's installation and calibration methods.

4.2. Technology Accuracy Analysis

In this section, the correlations between technology, methods, data, and filters are detailed to achieve the highest accuracy in various environments. This chapter will highlight the top 10 best correlations and the three worst correlations among these factors, focusing on those that yield the most accurate results in each environment. As shownin Figure 14, the accuracy results are not uniform depending on the technology used; indeed, for each technology, the accuracy value falls within a certain range.

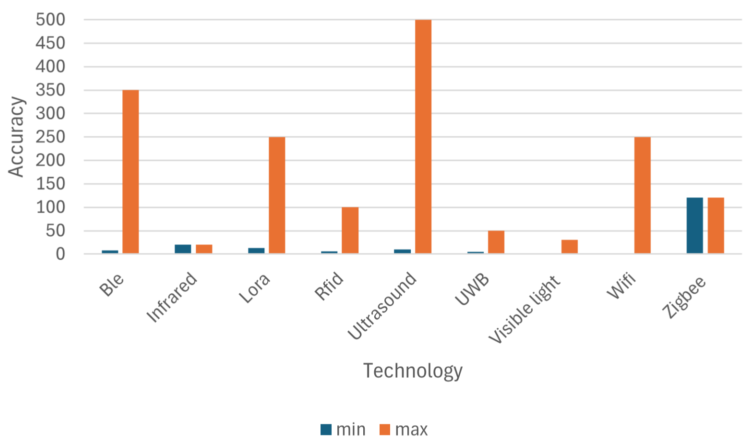

Figure 14. Minimum and maximum accuracy levels for indoor positioning technologies.

These variations in the range for the same technology occur because the technology is not the only factor that influences indoor positioning accuracy. It also depends on the method used for the geolocalization, the data used, the filters applied to the data, and the environment where it is used. As [108] notes, the environment has an impact on the accuracy results, such as interference from metal obstacles (racks, machinery, etc.) and metallic walls in industrial environments, which can reflect and block signals, thus causing deterioration in ranging and positioning accuracy.

Here is a detailed description of the columns and table contents analyzed in this chapter, which were examined for each type of environment:

- Reference paper: provides the bibliographical reference of the paper.
- Technology: lists the technologies used in each study for localization, including Wi-Fi, UWB, IMU, BLE, VLC, and RFID.
- Method: describes the methods used for localization, e.g., Multilateration, PDR (Pedestrian Dead Reckoning), closest neighbor, and digital map construction.
- Filters: specifies filters used to improve localization accuracy, such as EKF, KF (Kalman Filter), PF (Particle Filter), CNN, NN (Neural Network), and LSTM (Long Short-Term Memory).
- Data: indicates the types of data used for localization, such as PDoA (Phase Difference of Arrival), ToF (Time of Flight), CSI (Channel State Information), IMU data, RSSI (Received Signal Strength Indicator), and image data.
- Accuracy: provides the accuracy of the location obtained in each study, expressed in cm.

If the method is not present, a distance-based calculation approach was used to calculate the tag's position. This table is an invaluable resource for understanding which combinations of technologies and methodologies are most effective for achieving high accuracy in different environments, such as industrial settings, offices, supermarkets, and hospitals. Researchers and practitioners can use this information to guide future studies and implementations for improved positioning and tracking accuracy in similar settings.

4.2.1. Industrial Setting

Table 7 provides a structured summary of current technologies and methods for indoor localization in industrial environments, highlighting their evolution and the range of approaches that provide accuracies that range from 1.7 cm to 330 cm. These studies share the common aim of advancing indoor positioning precision by integrating cutting-edge technologies and techniques. Each approach reflects the underlying principle that combining technologies can overcome typical indoor localization challenges, such as multipath reflections and tracking errors. Key insights include the following:

1. Advanced filtering methods:
    - In [61,72,96], the authors focused on reducing errors using the EKF and particle filters, respectively. In [72], EKF improved localization accuracy, especially in orientation, reducing orientation error by approximately 0.5° to 1° with greater overall robustness.
    - In [39,49,108], the authors utilized machine learning techniques, specifically Convolutional Neural Networks (CNNs) and Neural Networks (NN), to process and filter data. In [108], the improvement led to an increase in accuracy by 29%. This highlights the growing role of machine learning in enhancing the accuracy of positioning systems.
2. Data accuracy:
    - Among the worst performances we found were those by [9,38,109,110], which all used the same RSSI data. Although low-cost to obtain, RSSI results are often unreliable. On the other hand, most of the best accuracy cases used ToF as data type [47,67,72,94,111].
3. Hybrid approaches:
    - Various studies have employed hybrid approaches by integrating multiple technologies. In [47,111], the authors utilized UWB and Inertial Measurement Unit

(IMU) sensors. In [94], the combination of UWB and BLE was used. Additionally, [9,109] featured the use of Wi-Fi and IMU sensors, while [38] combined UWB, BLE, and RFID technologies. These studies show how combining different technologies can enhance accuracy.

- Many studies combined multiple filtering techniques to enhance accuracy, such as KF and PF ([67]), NN and EKF [111], KNN and PF ([109]), CNN and KF [16,70], CNN and LSTM [38,47].

4. Technology accuracy:
    - In [47,67,94,108,111], the authors utilized UWB with favorable outcomes. As shown in Table 7, UWB is the most prevalent solution, yielding the highest accuracy results in industrial settings.

Table 7. Correlations in industrial settings.

Reference Paper	Technology	Method	Filters	Data	Accuracy
Best accuracies					
[72]	RFID	computer-based	EKF	ToF Image	1
[96]	Wi-Fi		EKF	PDoA	1.7
[67]	UWB	Multilateration	KF PF	ToF	5
[108]	UWB		CNN	CSI	6
[47]	UWB IMU	PDR Multilateration	CNN LSTM	ToF IMU	8
[39]	BLE	Multilateration	NN	RSSI	8
[61]	VLC	Closest neighbor	PF	IMU	10
[49]	VLC	Digital map construction	CNN	Image	10
[94]	UWB BLE	Multilateration		IMU ToF	10
[111]	UWB IMU	Multilateration	NN EKF	IMU ToF Image	13
[58]	RFID	Multilateration		PDoA	13
Worst accuracies					
[109]	Wi-Fi IMU	PDR Fingerprinting	KNN PF	RSSI	100
[9]	Wi-Fi IMU		KF	RSSI	120
[110]	BLE	Fingerprinting Multilateration	Chebyshev algorithm	RSSI	140
[38]	BLE UWB RFID		CNN LSTM	RSSI	200
[70]	UWB		KF CNN	ToA	300
[16]	UWB	Fingerprinting	KF CNN	TDoA	330

In industrial settings, different technologies and methodologies are favored:

- Ultra-Wideband: known for its precision in short-range tracking, UWB is frequently used in industrial settings.
- Multilateration: this method is commonly employed and consistently produces some of the best results. Moreover, Fingerprinting consistently yields the lowest accuracies.
- RSSI: this type of data obtained the lowest accuracies.
- Neural Networks and Extended Kalman filters: these are employed to process complex data and improve the accuracy of positioning systems.

In summary, industrial environments benefit most from technologies and methods that prioritize accuracy and robustness, such as UWB, multilateration, and advanced filtering techniques like neural networks and Extended Kalman Filters. By leveraging these approaches, practitioners can achieve greater precision and reliability in positioning systems, despite the challenges presented by industrial settings.

4.2.2. Office

As for the previous industrial setting section, we performed the same work for the office setting. Table 8 shows the combinations of different technologies, methods, filters, and data with the best and lowest accuracy achieved in the office testing environment. Each study is founded on the principle that combining multiple technologies and techniques can improve indoor positioning accuracy and help address common challenges in indoor positioning, such as environmental obstructions. Key insights include the following:

1. Advanced filtering techniques:
    - In [87], the authors used a computer vision system with a moving average (MA) filter to optimize inventory tracking. The application of the MA filter reduced random variations in the data, ensuring more stable and accurate tracking of objects in complex logistical environments.
    - In [92], the authors employed RFID technology, Multilateration, KF, and RSSI data, achieving high accuracy. The Kalman filter reduced noise in the data, improving the accuracy of the tracking system and making it more reliable even in environments with signal reflections.
    - In [84], the authors used NN and KF to improve the accuracy of UWB and TDoA systems. combining NN and KF allowed accurate position estimation.
    - In [85], the authors implemented a belief propagation algorithm (BP) and particle filtering based on Angle of Arrival (AoA) data.
    - In [83,112], the authors used Wi-Fi with the fingerprinting method and filters like KNN and Neural Networks. However, both experienced relatively low levels of accuracy, attributable to the complexity of the analyzed environments, which are characterized by numerous interferences and reflections that negatively affect system performance.

    These studies show that although advanced filters such as Kalman filtering, particle filtering, and neural networks can significantly improve accuracy, the results are influenced by the type of technology and the specific environment in which they are applied.
2. Geometric methods:
    - In [104], the authors used a hyperbolic method with a moving antenna, utilizing TDoA data and Particle Swarm Optimization (PSO).
    - In [102], the authors used a geometric method of hyperbolic intersection for position calculation.
    - In [98], the authors employed hyperbolic intersection.

    These studies underscore the effectiveness of multilateration techniques in enhancing positioning accuracy.
3. Methods' combination:
    - In [87], the authors used two methods, such as Centroid Localization Method (CLM) and a computer-based approach. This hybrid combination suggests that

the use of multiple methods can enhance the localization system's accuracy by utilizing each technology's strengths to achieve better results.

4. Data accuracy:
   - In [102,104] and [84], the authors utilized TDoA, which is the most frequently used data among the examples which yield superior accuracy results.
   - In [69,83,112], the authors used RSSI data, which had lower accuracy.
5. Hybrid technologies approaches:
   - In [83,102], the authors employed LORA and a UWB or Wi-Fi system. The study revealed that LORA paired with UWB achieved superior accuracy compared to the Wi-Fi combination.
   - In [84], the authors used UWB with an inertial sensor IMU, achieving high accuracy. This approach demonstrates the advantages of incorporating IMU data to enhance stability and accuracy, particularly in environments with dynamic or complex layouts where positional data may otherwise degrade.
6. Technology accuracy:
   - In [56,98,104], the authors used RFID technology, achieving good accuracy, and it is the most used in offices.

Table 8. Correlations in offices.

Reference Paper	Technology	Method	Filters	Data	Accuracy
Best accuracies					
[87]	VLC	CLM computer-based	MA	Image	1
[113]	VLC			Image	1
[48]	RFID		PF	PDoA	2
[114]	Radio-based		UKF		4
[98]	RFID	Multilateration		PDoA	6.5
[88]	Ultrasound	Multiangulation	low pass	AoA	10
[92]	RFID	Multilateration	KF	RSSI	10
[85]	VLC	BP	PF	AoA	10
[104]	RFID	Multilateration	PSO	TDoA	12.2
[102]	UWB LORA	Multilateration	MA	TDoA	13
[84]	UWB IMU	Multilateration	NN EKF	IMU TDoA	14
[56]	RFID	ML		PDoA	20
Worst accuracies					
[115]	RFID	Fingerprinting	NN	RSSI	150
[112]	Wi-Fi	Fingerprinting	KNN genetic	RSSI	250
[83]	Wi-Fi LORA		NN	RSSI	250
[69]	BLE	Closest neighbor		RSSI	350
[78]	Ultrasound	Fingerprinting	KF median filter	IMU	500

In office settings, different technologies and methodologies are favored:

- RFID: commonly used for tracking objects and people, RFID systems are highly effective in office environments.
- Multilateration: it provides good accuracy with RFID technology on campuses, while Fingerprinting does not have good results.
- EKF: this algorithm is used to predict and correct positions, enhancing accuracy.
- Time difference of arrival (TDoA): This method uses the time difference between received signals to determine position, providing reliable results. On the other hand, RSSI achieves the lowest accuracy.
- Hybrid approaches: The combination of hybrid technologies and methods tends to produce lower accuracy results.

This analysis helps practitioners understand various ways to implement indoor positioning technologies in this environment to achieve favorable results, which is crucial for logistics applications.

4.2.3. Supermarket

The articles in Table 9 are connected in that they address the issue of localization and tracking within indoor environments using different Radio Frequency Identification (RFID) and Bluetooth technologies, as well as machine learning methodologies:

1. Supermarket [26,59]: In [26], the authors used RFID technology with Angle of Arrival (AOA) data to determine the position of a person wearing the RFID reader, with tags placed on the shelves. This method aims to send personalized advertisements to individuals approaching certain areas of the supermarket, enhancing customer interaction and potentially increasing sales. In [59], the authors achieved a positioning accuracy of 1.05 m in the optimal scenario (using 341 reference points) and 4.62 m in the least favorable scenario (using 45 reference points).
2. Library [53]: The authors used RFID technology, along with RSSI and phase data to calculate the absolute position of RFID tags through multilateration. Additionally, a CNN is utilized to establish the relative position of the tags and compute the z-coordinate (height). This method is useful for precise inventory management and object localization within a library, facilitating book management and retrieval.
3. Museum [52]: The authors utilized Bluetooth technology, RSSI data, and a neural network filter to track positions. Although this method achieved lower accuracy compared to other approaches, it is still useful in a museum context for tracking visitors and interacting with exhibits, thereby enhancing visitor experience.

In summary, these articles share the common goal of improving indoor localization and user interaction through the use of RFID and BLE technologies, each applied to a specific context (supermarket, library, museum). The main differences lie in the technologies used (RFID vs. Bluetooth), the methods for position calculation (AOA, RSSI, phase), and the specific applications in various scenarios. AOA outperformed RSSI, and Multilateration outperformed Fingerprinting in this environment.

Table 9. Correlations in supermarkets.

Reference Paper	Technology	Method	Filters	Data	Accuracy
[26]	RFID	Multiangulation Digital map construction	Moving average	AoA	10
[53]	RFID	Multilateration	CNN	RSSI Phase	25
Worst accuracies					
[52]	BLE		NN	RSSI	100
[59]	Radio-based	Fingerprinting	KNN Chebyshev algorithm	RSSI	460

4.2.4. Hospital

For hospitals, only one article was found: In [20], the authors used tag bracelets with RFID technology, RSSI signal, and trilateration methods to track the location of elderly people. Antennas were required in each room of the hospital for the data to be detected. The article does not mention the accuracy of this tracking method.

5. Discussion

Building on the findings in prior sections, we summarize the answers to the five proposed research questions. The first two questions are as follows: "Which IPSs exist in the literature?" (RQ1) and "Which IPSs are most commonly used in logistics, depending on the environment in which they are tested?" (RQ2). These environments include industrial settings, offices, hospitals, and supermarkets. In response to RQ1 and RQ2, we identified that radio-based technology is the most prevalent across all environments, in alignment with existing literature, as confirmed in [34] individuated. Among radio-based options, RFID is the most frequently used technology, in line with current literature and as illustrated in [81] and shown in Figure 9. Specifically, UWB, RFID, and BLE are widely used in industrial settings; RFID, Wi-Fi, and UWB in offices; RFID in hospitals; and RFID and BLE in supermarkets. Geometric methods, particularly multilateration (Figure 11), are the most common in each setting, as noted in [34], followed by fingerprinting. Across environments, the majority of studies employ signal characteristic-based data, while time-based and motion-based data are common in industrial settings and offices. In supermarkets, angle-based and signal data are primarily used. Enhanced accuracy and reliability can be achieved by combining these technologies with advanced filtering techniques or machine learning models. The most widely used parametric filtering methods are particle filtering, Extended Kalman Filter in industrial settings, and Kalman filtering in offices. Convolutional Neural Networks, Neural Networks, and k-nearest neighbors.

The third question, "What are the aims of the reviewed contributions?" was addressed by categorizing these objectives into four areas: material flow control, intralogistics design and management, safety, and accuracy testing. Our analysis (Figure 7) shows that the majority of contributions (56%) focus on accuracy testing, emphasizing the importance of evaluating IPS performance before practical logistical applications. The remaining 44% address practical applications, with 20% focused on material flow control, 18% on intralogistics design and management, and 6% on safety. This indicates that future research should focus on exploring the impact of IPS in practical logistics applications, particularly in safety, an important but underexplored area within the Industry 5.0 framework [116–118]. The fourth and fifth questions ask, "What IPS pairings were utilized?" (RQ4) and "What accuracy does a specific IPS achieve based on the environment in which it is used?" (RQ5). Our findings for RQ4, detailed in Tables 7–9, illustrate correlations between technologies, methods, filters, and data. Moreover, Table 4 highlights the combination of Inertial Measurement Units (IMU) with radio-based technologies, as previously demonstrated in [36], which underscores its benefits in enhancing IPS performance. Combining diverse technologies is a powerful approach to achieving optimal accuracy and reliability for indoor positioning across various environments. In response to RQ5, we found that different technologies and combinations thereof yield varying accuracy levels. According to Figure 14, technologies like visible light, infrared, UWB, and RFID offer the highest accuracy, while BLE, Wi-Fi, and LoRa demonstrate medium to low accuracy; Zigbee falls in the medium accuracy range [32]. Generally, as shown in Tables 7–9, UWB obtains higher accuracy in industrial environments, while RFID excels in offices. On the other hand, RSSI, Wi-Fi, and BLE in industrial and office settings tend to be less accurate, while time-based data performs exceptionally well, as illustrated in Table 5. Furthermore, geometric methods consistently deliver better accuracy across settings (as shown in Tables 7–9). The broad range of accuracy values highlights that IPS precision is highly affected by environmental conditions. Real-world IPS implementation poses challenges, particularly in device installation, calibration, and data processing due to environmental interferences. For example, [7] explored sensor placement and found that lower heights increase the chance of encountering Non-Line of Sight (NLOS) conditions due to interference. The geometry and size of the area between anchors, or the "cell", also affect accuracy due to hidden areas and signal attenuation. Physical [14] and electromagnetic interference [5] further complicate successful IPS deployment. Electromagnetic interference from industrial machinery or electronic devices, as noted by [30], and physical obstacles like walls and metal shelves can alter signal propagation, causing reflections and attenuations that reduce measurement accuracy. Additionally, materials such as wood or plastic absorb Wi-Fi signals, which degrades measurement quality and Wi-Fi-based IPS accuracy. We examined how IPSs can be effectively employed in logistics across different environments, including industrial settings, offices, hospitals, and supermarkets, despite multiple interferences. We found that sensor fusion techniques can help address these interferences in line with [33]. Hybrid positioning systems enhance accuracy by combining the strengths of various technologies to overcome environmental challenges.

IPSs have attracted growing interest, especially radio frequency technologies, due to their transformative potential across multiple sectors [36]. However, more research is needed to fully explore and optimize these technologies for specific applications. Despite rising interest, there remains a significant lack of research on IPS in particular settings, such as hospitals and supermarkets. Future studies could address this gap by examining the benefits of patient geolocation in hospitals or cart tracking in supermarkets. In hospitals, IPS could improve patient safety through real-time tracking, expedite response times during emergencies, and optimize medical equipment use, as discussed in [20]. In supermarkets, tracking shopping carts could streamline operations, enhance customer service, and provide valuable insights for inventory and marketing, as noted by [26]. Further research on IPS for logistics applications is also needed, particularly for intralogistics design, management, and material flow control. Effective IPS implementations, as discussed by [79], could lead to optimized warehouse layouts, identify bottlenecks, and improve route definitions, resulting in enhanced efficiency, cost savings, sustainability, and operational performance. Further research in logistics should also focus on integrating IPS with software expert systems aiming at decision support [119], mainly related to customers´ requirements regarding due date, quantity, and mix of deliveries. Future studies should also investigate the impact of environment dimensions and device count on testing outcomes. Addressing these research gaps will support the development of more effective and customized IPS solutions, ultimately enhancing safety, efficiency, and performance across various sectors.

6. Conclusions

The integration of IPS into logistics operations represents a significant advancement, underscoring its critical importance in modern logistics management, as discussed by [32]. Our contribution aims to assist practitioners in utilizing IPS for various logistics applications, including safety, intralogistics design and management, and material flow control. Additionally, some studies focus on accuracy tests to evaluate the application of IPS in logistics. Our review covers technologies, methods, data, filtering techniques for improving output, various hybrid technologies, and examples of IPS applications. Understanding how IPS function is essential for its implementation in a logistics context where accuracy is typically paramount. Given that interferences vary across different environments, we differentiated settings such as industrial facilities, offices, supermarkets, and hospitals. Notably, the same technology produced different results, depending on the environment (see Figure 14). We found that UWB technology was primarily used in industrial environments, which yielded the best results, while RFID was favored in other settings (see Figure 9). Overall, visible light, UWB, and RFID demonstrated the highest accuracy values (see Figure 14). Geometric methods consistently provided the best results across all environments (see Tables 7–9). Moreover, certain data types proved to be more effective than others, with RSSI showing the lowest accuracy (see Tables 5 and 7–9). Regarding the filtering techniques, EKF, and particle filtering, CNN and NN are the most used in industrial settings, while KF, CNN, and NN are the most common in offices (see Figures 12 and 13).

Conversely, the accuracy results from the studies indicated similar accuracy levels across different environments, with most results falling between 1 and 99 cm (see Table 6). This consistency was achieved by mitigating obstructions through the use of hybrid approaches, which integrate different technologies, filters, methods, and data.

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Abbreviations

The following abbreviations are used in this manuscript:

AGVs	Automated Guided Vehicles
AoA	Angle of arrival
AoD	Angle of departure
BLE	Bluetooth Low Energy
BP	Belief propagation
CLM	Centroid Localization Method
CNN	Convolutional neural network
CSI	Channel state information
EKF	Extended Kalman Filter
IMU	Inertial Measurement Unit
INS	Inertial navigation system
IPS	Indoor positioning systems
KF	Kalman Filter
KNN	K-nearest neighbor
LORA	Long Range
LSTM	Long short-term memory
MA	Moving average
MAVs	Micro aerial vehicles
ML	Maximum Likelihood
NN	Neural network
PDoA	Phase difference of arrival
PDR	Pedestrian Dead Reckoning
PSO	Particle Swarm Optimization
RFID	Radio Frequency Identification System
RSSI	Received signal strength indicator
RTLS	Real-time location systems
SVM	Support Vector Machine
TDoA	Time difference of arrival
ToA	Time of arrival
ToF	Time of flight
UAVs	Unmanned aerial vehicles
UAS	Unmanned aircraft system
UHF	Ultra High Frequency
UKF	Unscented Kalman Filter
UWB	Ultra-Wideband

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