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Review Paper

Indoor positioning systems in industry 4.0 applications: Current status, opportunities, and future trends

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ABSTRACT

In the context of Industry 4.0, the precise location information of resources is fundamental for orchestrating myriad operations and processes. In outdoor environments, the Global Navigation Satellite System (GNSS) provides universal positioning, navigation, and timing services to users worldwide. Nevertheless, GNSS signals are severely obstructed and interfered with indoors, rendering the system ineffective in such environments. Notably, most Industry 4.0 settings, such as shopfloors, warehouses, and production sites, are in indoor or semi-indoor environments, where structures and means of production elements can obstruct or interfere with GNSS signals. Therefore, GNSS cannot fully meet the precise positioning requirements of Industry 4.0. Indoor Positioning Systems (IPS) can effectively compensate for the limitations of GNSS to enable the identification and tracking of precise object position within indoor or semi-indoor environments. Over the past decade, substantial research on IPS has been conducted within the academic and industrial sectors, with findings disseminated across numerous academic journals. However, there remains a notable absence of comprehensive reviews on IPS from an Industry 4.0 perspective to date, as well as any distillation of the functionality of IPS in industrial scenarios. This paper offers an exhaustive review of state-of-the-art IPS research and categorizes IPS applications as resource management, production management, and safety management to bridge this gap. The goal is to assist researchers and industry stakeholders in recognizing current research gaps, grasping the content of IPS theory, appreciating its industrial applications, and charting paths for future scholarly inquiry. This work potentially provides an innovative spatial-temporal framework for the technology-centric focus of Industry 4.0 or even insights into the value-driven perspective of Industry 5.0.

1. Introduction

In the era of Industry 4.0, production operations must continue to improve efficiency, flexibility, and collaboration to drive mass customization [1]. Enterprises need to have a higher degree of production automation and process flexibility to improve their internal product production capacity and ability to cope with external uncertainty to meet customer demand for high-quality and customized products. In the case of dynamic shop floor environments with many randomly fluctuating customer orders and resource availability, traditional scheduling rules and heuristic algorithms cannot solve the production planning and control problem well [2]. Acquiring real-time location information of production resources, which can realize the spatial-temporal traceability and visibility of objects, is foundational for enterprises to efficiently orchestrate different production processes and effectively improve dynamic responsiveness. Spatial-temporal traceability allows for extracting valuable insights from historical trajectory data, facilitating more efficient resource allocation and bottleneck identification. Spatial-temporal visibility empowers enterprises to monitor the physical processes across various stages - planning, scheduling, and execution – and to make timely adjustments in response to dynamic demand and production status, which leads to more flexible, intelligent, and reconfigurable production processes. Such advancements are instrumental in achieving digitization, automation, and adaptability.

The physical and virtual worlds must be tightly integrated and synchronized to achieve visibility and traceability from a spatial-temporal

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perspective. Digital twins (DTs), a key enabling technology for Industry 4.0, are a core method for integrating the physical and virtual worlds [3]. In virtual space, based on the attributes of physical entities, the digital twin model can be expressed in four model dimensions: geometric, physical, behavioral, and rule [4]. DTs can iterate and evolve through seamless connection and fusion between virtual and physical spaces, and this consistency and synchronization can bring many benefits to a wide range of services, including real-time monitoring, dynamic optimization, and accurate prediction [5,6]. Positioning systems, which accurately identify and track the location of an object in the physical world and project it into the virtual space, are the only way to realize DTs at the spatial-temporal level. Based on different techniques and methods, positioning systems can realize relative and absolute positioning of objects in two-dimensional or three-dimensional space. Relative positioning is suitable for application scenarios that require relative position information, while absolute positioning techniques can provide information about the position of an object in a global coordinate system. In addition, the positioning system has diversified positioning accuracies, such as centimeter-level, meter-level, or ten-meter-level, which can meet the needs of different application scenarios for positioning accuracies.

The mature outdoor positioning system, namely the Global Navigation Satellite System (GNSS), has achieved sub-meter positioning accuracy in outdoor environments [7]. GNSS, including various outdoor positioning systems such as GPS, GLONASS, Galileo, and BeiDou [8], provides users worldwide with universal positioning, navigation, and timing services. However, GNSS cannot provide services with high accuracy in the presence of GNSS signal occlusion in the environment. Coincidentally, most Industry 4.0 scenarios (e.g., workshops, warehouses, and sites) are predominantly indoors or semi-indoor environments, where a variety of buildings (e.g., walls, roofs, rebars) and production materials (e.g., people, equipment, materials) can potentially result in signal attenuation, multipath effects, and electromagnetic interferences. Consequently, GNSS cannot fully meet the positioning needs of Industry 4.0 contexts. With the improvement of wireless communication, sensor technology, and data processing capabilities, indoor positioning systems (IPS) have made remarkable progress. IPS can provide more accurate and reliable positioning services, effectively compensating for the shortcomings of GNSS, realizing the identification and tracking of object location, and providing technical support for indoor and semi-indoor scenes like construction sites to achieve seamless real-time positioning [7]. IPS need more attention to develop ubiquitous, integrated, and intelligent spatial-temporal frameworks suitable for Industry 4.0 environments.

The IPS-related research and applications help enterprises effectively monitor, predict, plan, and optimize production processes. First, IPS provides real-time monitoring and tracking capabilities, enabling organizations to know the location and activities of their personnel, equipment, and materials to make timely adjustments and decisions. Second, IPS helps organizations eliminate uncertainties in the production process and improve the controllability and stability of the process. Third, location information from IPS can be used for data analysis and modeling to help companies forecast and plan, optimize resource allocation, and develop production schedules. Finally, integrating IPS with automation systems can realize intelligent production processes and equipment control to improve production automation. In addition, the concept of internet of everything was proposed in 2017 [9]. Location awareness is receiving increasing attention in the industry.

There are some review articles in the field of IPS. However, most indoor positioning research focuses on the indoor positioning technology itself [10–13]. Although there have been attempts to introduce IPS into industrial applications [14–16], they have focused more on locating targets in industrial scenarios but do not integrate IPS with real-time decision-making regarding resource management, production management, and safety management in industrial applications. Therefore, serious deficiencies in the mining, utilization, and integration of spatial-temporal information and the corresponding location-based services still need further development and improvement.

Therefore, this paper aims to provide a comprehensive literature review of the current applications of IPS across various aspects in the context of Industry 4.0. First, we synthesize the scholarly literature on indoor positioning technologies, techniques, machine learning applications within IPS, and assessment metrics, published between 2014 and 2023. Then, the applications of IPS in different industries are summarized and compared in the context of Industry 4.0. Subsequently, we identify prospective directions for applying indoor positioning systems to solve industrial problems. The review will serve to pinpoint potential avenues for future research. Furthermore, it will enable industrial practitioners to develop a more profound and nuanced understanding of the relationship between IPS and industry, thereby assisting them in devising more effective execution strategies leveraging IPS technologies. The significance of this work lies in its capacity to shed light on the evolving applications and development of IPS within the Industry 4.0 landscape. The primary contributions of this paper are threefold. Firstly, it generates novel perspectives for scholars and practitioners engaged in the field of IPS research, furnishing them with fresh ideas and avenues for exploration. Secondly, the work offers practical guidelines to facilitate the industrial application of IPS, providing actionable recommendations for professionals seeking to implement these technologies within their operational contexts. Thirdly, this review elucidates the evolving role of IPS within the broader framework of Industry 4.0, illuminating their integral contributions to the domains of resource management, production processes, and safety protocols. To this end, this paper identifies the following three research questions:

(i) What are the proper technologies and techniques of IPS under various Industry 4.0 settings?
(ii) How can the realization of IPS contribute to the successful implementation of Industry 4.0?
(iii) What are the challenges and future directions for the IPS from Industry 4.0 to Industry 5.0 era?

The rest of the paper is structured as follows. Section 2 introduces the main research methodology and research framework. Section 3 summarizes the techniques, methods, and evaluation metrics related to indoor positioning and the application of machine learning in indoor positioning. Section 4 summarizes the application of indoor positioning systems in industry in the context of Industry 4.0. Section 5 presents the future work, and Section 6 concludes the full paper.

2. Research method

2.1. Selection and analysis of reviewed samples

A search based on “title/abstract/keywords” was performed to conduct a comprehensive literature search using prominent search engines such as Web of Science, Scopus, IEEE, EI, Elsevier, and Taylor & Francis databases. Technical keywords include but are not limited to “indoor positioning,” “indoor positioning system,” “real-time positioning system,” “location system,” “location-based system,” “location-based system,” “location-based system,” “location-based system,” “location-based system,” “location-based system,” “location-based system,” “location-based system,” “location analytics,” “real-time tracking” and “traceability and visualization.” Application keywords include but are not limited to “manufacturing,” “logistics,” “construction,” “production,” “intra-enterprise logistics,” “warehousing,” “factory,” “shop floor” and “construction site.” The obtained search results were compiled into lists of papers for potential review.

However, upon closer examination of the extensive list, it became apparent that different journals often have specific publishing interests, and the choice of journal significantly influences the range of research topics covered. Consequently, the investigation was restarted and narrowed down to research articles published in renowned and influential journals. Referring to Xue et al. 's selection criteria of journal selection [17], our journal selection criteria were as follows: (1) the journal was included in the citation database SCI-expanded database; and (2) the journal has a significant impact and is unanimously recognized in the field of construction, manufacturing, and logistics research. Therefore, we carefully selected 15 journals to capture the critical papers in the chosen domain. The selected journals are Advanced Engineering Informatics, Journal of Computers in Civil Engineering, Automation in Construction, Journal of Construction Engineering and Management, Journal of Computer-Aided Civil and Infrastructure Engineering, International Journal of Production Economics, Journal of Manufacturing Systems, Robotics and Computer-Integrated Manufacturing, Journal of Industrial Information Integration, Computers and Operations Research, Computers and Industrial Engineering, Advanced Engineering Informatics, Journal of Intelligent Manufacturing, International Journal of Production Research, and Safety Science, which are recognized by the research community as outstanding, high quality, and having a significant impact in the field.

To conduct a more focused and comprehensive search, the target journals were thoroughly explored using the Scopus/SCI search engine. This approach ensured a more extensive coverage of relevant research articles within the selected journals. Based on Gu et al.'s [18] survey, five IPS-related technologies were selected for review, including radio frequency identification (RFID), ultra-wideband (UWB), Bluetooth Low Energy (BLE), Wireless Fidelity (Wi-Fi), and ZigBee. The entire literature search methodology is shown in Fig. 1, where a combination of technologies, industries, databases, and article content is used to finally select the literature that meets the objectives of the article.

This study identified and reviewed 849 relevant papers published between 2014 and 2023 through a systematic literature search. After careful selection, a sample of 175 articles highly relevant to the study objectives was identified in Table 1 for in-depth analysis.

In terms of the distribution of literature types, journal articles dominated the sample, with a high percentage of 69 %. Among them, articles from seven core journals such as Automation in Construction, Journal of Manufacturing Systems, Advanced Engineering Informatics, International Journal of Production Economics, Robotics and Computer-Integrated Manufacturing, Journal of Intelligent Manufacturing, and Computer & Industrial Engineering accounted for 28 %. This indicates that these journals have strong academic influence in the field and

Table 1
Analysis of IPS-related articles in the context of Industry 4.0 from 2014 to 2023.

Type	Name	Number of articles	% of 175
Journal	Automation in Construction	14	8 %
	Journal of Manufacturing Systems	8	5 %
	Advanced Engineering Informatics	7	4 %
	International Journal of Production Economics	6	3 %
	Robotics and Computer-Integrated Manufacturing	6	3 %
	Journal of Intelligent Manufacturing	5	3 %
	Computers & Industrial Engineering	4	2 %
	Other	71	41 %
Conference	/	54	31 %
Total		175	100 %

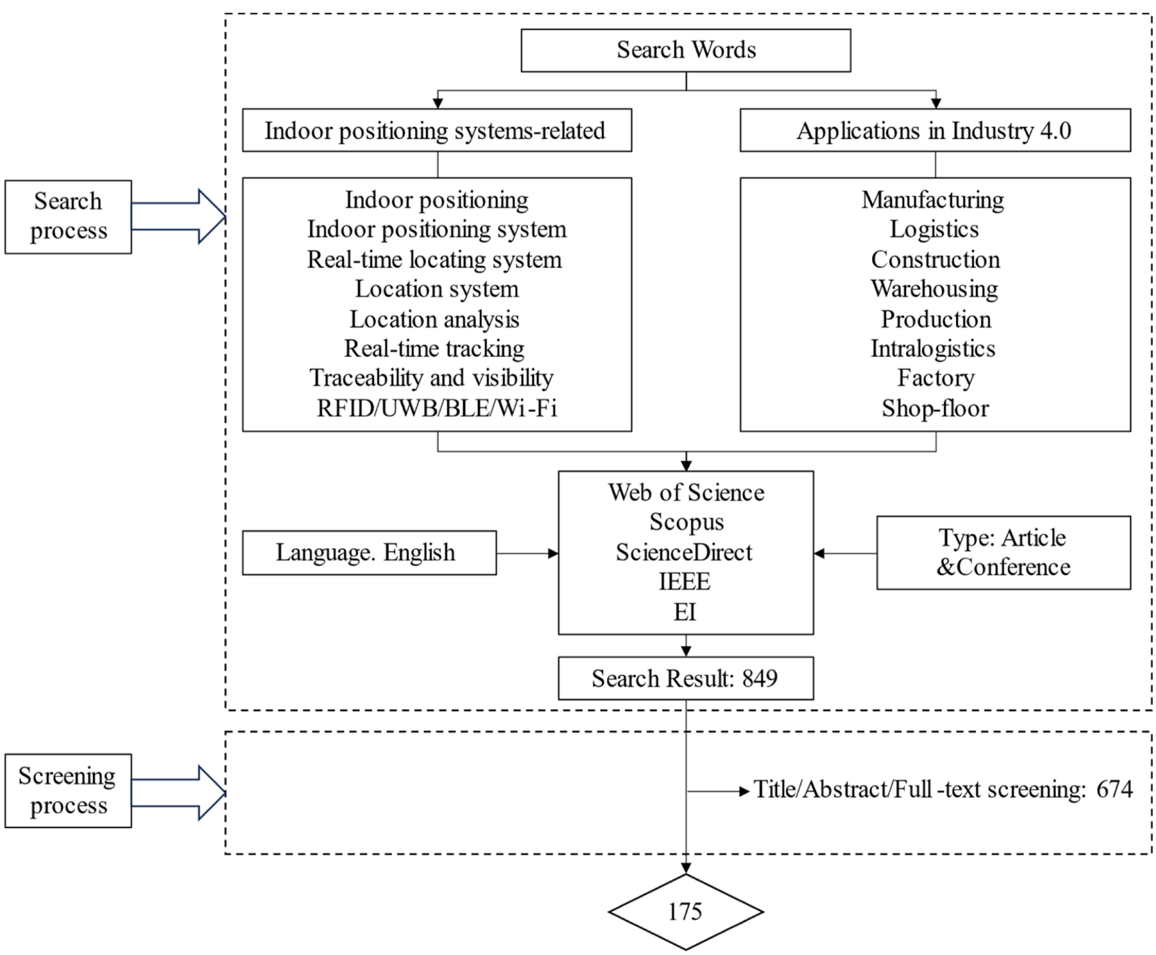

Fig. 1. Systematic literature review stages.

become the preferred publication platforms for scholars. The remaining 41 % of the journal articles show a high degree of dispersion, highlighting the wide dissemination of knowledge in this research area. It is noteworthy that conference papers also account for a significant proportion of the total literature, as high as 31 %. This reflects that the academic community actively participates in academic exchanges and conducts extensive and in-depth discussions on related topics.

In general, this research area is characterized by the dominance of journal papers, the concentration of core journals, and the significant contribution of conference papers. This provides a rich knowledge base for subsequent research and demonstrates the positive attitude of scholars to continue to promote the development of this field.

2.2. Overview of IPS in Industry 4.0

Businesses today face a myriad of novel challenges amidst the backdrop of progressive globalization, mass customization, and intensified competition. The urgent demands for accelerated delivery, streamlined automated processes, superior product quality, and personalized offerings have propelled organizations to embrace the paradigm of Industry 4.0 [19]. Industry 4.0 is characterized by the strategic integration of emerging communication, information, and intelligence technologies to enhance flexibility, efficiency, and productivity in manufacturing processes [20]. Of paramount importance is the availability of spatial-temporal data pertaining to manufacturing resources, encompassing the physical movements of products, devices, materials, and personnel, as well as the precise timing and location of information generation and transactions. By obtaining this spatial-temporal data, manufacturers can establish accurate references to guide their planning, scheduling, and execution activities. Furthermore, the adoption of a standardized representation of real-time resource status plays a pivotal role in facilitating intuitive visualization and promoting seamless compatibility among industry stakeholders. This standardization is essential for effective monitoring and swift intervention during emergencies, such as timely collision warnings, personnel anomaly detection and rescue, hazardous area identification, and urgent notifications. Spatial-temporal traceability also enables the examination of resource movement and interaction patterns over time, thereby empowering the identification of production bottlenecks. These bottlenecks may arise from factors such as inefficient process scheduling, suboptimal site layouts, inadequate staffing arrangements, and inefficient material flow routes. By promptly detecting such bottlenecks, traceability equips production control to implement necessary measures swiftly, including real-time resource scheduling to achieve maximum efficiency and minimal cost. Through effective traceability reasoning, resources can gain situational awareness and proactively respond to events, facilitating more rational inventory management and allocation. Moreover, logistics hubs, distribution centers, and assembly lines must establish buffer spaces during peak hours to accommodate resource complexity and unexpected disruptions, such as material shortages and urgent orders. The geographic distance between objects in these buffer spaces and their order of picking significantly impact both time and costs. Optimizing the coordination between the spatial and temporal dimensions of resources is crucial for realizing zero inventory [21] or even zero warehousing [22].

DTs, a core enabling technology for Industry 4.0, serve as a fundamental methodology for seamlessly integrating the physical and virtual worlds [3]. The vision of DTs is to offer a comprehensive representation encompassing the physical and functional characteristics of a component, product, or system [23]. The initial and paramount step in this process involves the development of high-fidelity virtual models that accurately replicate the geometry, physical properties, behaviors, and governing principles of the physical world [24]. These virtual models exhibit a high level of consistency with physical components in terms of their geometry and possess the ability to simulate their spatial-temporal states, behaviors, functions, and other relevant characteristics [25]. Furthermore, models within digital environments can optimize operations and directly adjust physical processes through real-time feedback mechanisms [26]. Through the utilization of bidirectional dynamic mapping, physical entities and virtual models undergo a process of co-evolution [27]. The virtual model integrates geometric, structural, behavioral, rule-based, and functional attributes to represent specific physical objects with high accuracy and fidelity. In this context, positioning systems emerge as the critical enabler for realizing the spatial-temporal fidelity of DTs. By efficiently and accurately capturing the location information of resources in the physical world and projecting it into the virtual space, IPS play a pivotal role in establishing the necessary spatial-temporal linkages between the physical and digital domains in Industry 4.0 settings, as shown in Fig. 2. This integration is fundamental to realize the vision of DTs, as it allows for the seamless synchronization and co-evolution of the physical and virtual realms, unlocking the transformative potential of Industry 4.0.

Nonetheless, significant challenges remain in achieving a comprehensive spatial-temporal framework within Industry 4.0 scenarios. Firstly, as most Industry 4.0 activities occur indoors, conventional outdoor positioning systems are ill-suited for indoor use. The absence of widely adopted standards for expression, interoperability, and data sharing prevents the achievement of robust spatial-temporal traceability and visibility within indoor environments. Secondly, positioning accuracy is severely compromised in industrial settings due to the prevalence of multipath effects and signal fading. Furthermore, changes in the environment over time lead to a decline in accuracy, necessitating labor-intensive and time-consuming recalibration whenever environmental conditions change. This makes the development of environment-specific localization models an arduous and ongoing challenge. Thirdly, while spatial-temporal information about manufacturing resources offers valuable insights for optimization and decision-making at the operational level, the lack of comprehension regarding patterns and trends occurring in time and space hampers the development of genuinely informed and predictive decision-making processes. As a result, there is a pressing demand for focused research on IPS. This research should involve the systematic organization and evaluation of various IPS, as well as the selection of suitable positioning techniques and methods that can meet the accuracy requirements of real-world scenarios (such as area positioning, orientation positioning, and precise positioning). Simultaneously, the integration of robust data processing, analytical analysis, and advanced machine learning techniques is essential. This will enable the precise capture of spatial-temporal information related to manufacturing resources, the establishment of standardized spatial representation and temporal measurements for these resources, and the assurance of accurate and enduring indoor positioning capabilities. Moreover, the employment of spatial-temporal reasoning mechanisms can help mitigate the impact of resource complexity and unexpected disturbances that arise during operations within the context of Industry 4.0. These spatial-temporal reasoning mechanisms can serve as a bridge, facilitating the transition from the technology-centric perspective of Industry 4.0 to the value-driven perspective of Industry 5.0 [28].

3. Overview of indoor positioning methodologies

The analysis of the 175 screened documents, as presented in Table 2, reveals the technological landscape of IPS research over the past decade. RFID technology stands out as the most widely studied, with 81 articles accounting for nearly 46 % of the total. This reflects the widespread application and central role of RFID in IPS. In contrast, ZigBee technology has been relatively neglected, with only 3 articles, possibly due to its limitations in coverage and positioning accuracy in practical applications. Beyond the individual technologies, the research landscape also includes 9 articles exploring hybrid positioning approaches and 18 articles focusing on the overall framework and applications of IPS, indicating researchers' efforts to develop more complex and comprehensive solutions. Table 2 also highlights the temporal trajectory of IPS-

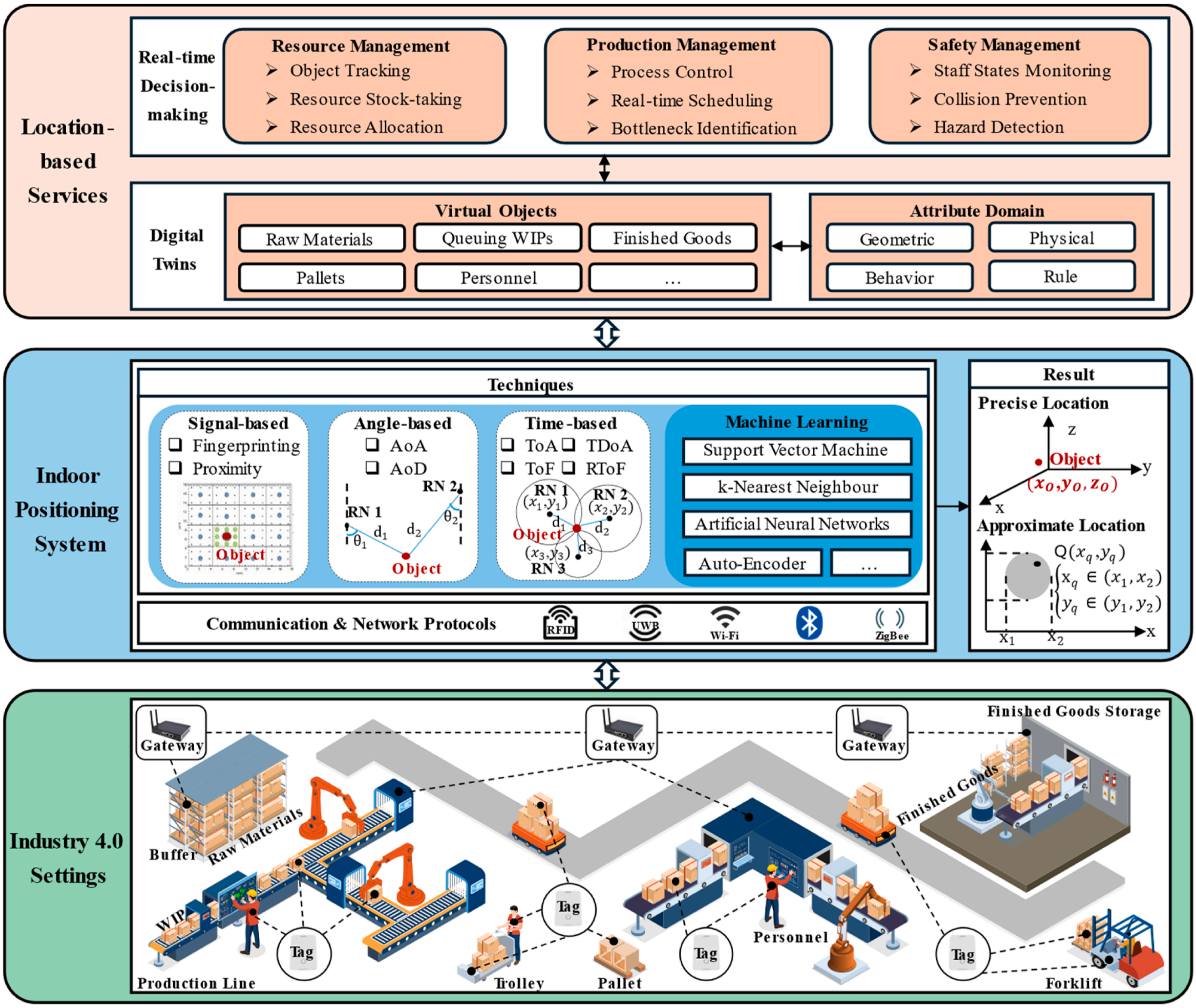

Fig. 2. The overview of IPS for applications in Industry 4.0.

Table 2
Distribution of technology-based reviewed articles.

Year	RFID	BLE	UWB	Wi-Fi	ZigBee	Hybrid	IPS	Total
2014	4	–	–	–	–	–	–	4
2015	7	–	1	–	1	–	–	9
2016	7	2	1	–	–	–	–	10
2017	10	–	1	–	–	1	–	12
2018	10	3	1	2	1	–	–	17
2019	13	1	1	–	–	1	1	17
2020	14	2	1	–	–	3	3	23
2021	5	7	7	1	–	1	4	25
2022	5	7	10	–	1	3	1	27
2023	6	8	5	3	–	–	9	31
Total	**81**	**30**	**28**	**6**	**3**	**9**	**18**	**175**

related research literature. Over the past 10 years, the number of articles has grown continuously, with the volume in 2023 already about eight times that of 2014. This trend suggests that the IPS field is attracting increasing attention and enthusiasm in the academic community, and the research is becoming more in-depth and mature. In terms of research methodology, more than half of the literature adopts an experimental validation approach, reflecting researchers' emphasis on the feasibility and performance of IPS technology in practical application scenarios. This is further reinforced by studies ([29,30,31]), which have been tested and applied in real-world environments, enhancing the practicality and relevance of the research.

Notably, the IPS technology serves as the physical foundation for realizing positioning functionalities. It encompasses a range of wireless communication technologies, including RFID, BLE, UWB, Wi-Fi, and ZigBee. These technologies leverage the physical characteristics of wireless signals, such as signal strength, angle, and propagation time, to obtain the information required for positioning. Correspondingly, the IPS technique refers to the mathematical models and algorithms developed based on the characteristics of these technologies. They encompass various positioning algorithms that utilize physical quantities like signal strength, angle, or time, including Received Signal Strength Indicator (RSSI), Angle of Arrival (AoA), Time of Arrival (ToA), and Time Difference of Arrival (TDoA). These positioning techniques rely on mathematical modeling and analysis of the physical properties of wireless communication technologies to estimate and project the target position. Fundamentally, the technology focuses on the physical implementation at the lower layer, while the technique focuses on the mathematical modeling at the upper layer. The technology provides the physical foundation for positioning, while the technique ensures the realization of positioning functionalities. The synergistic combination of technologies and techniques facilitates the construction of more accurate and reliable IPS.

The subsequent sections will introduce the methods and technologies of indoor positioning, their integration with machine learning, and the evaluation metrics of IPS.

3.1. Technologies

In this paper, five technologies, including RFID, BLE, UWB, Wi-Fi, and ZigBee, are selected for the study. As detailed in Table 3, each technology exhibits varying levels of accuracy, energy, cost, and scalability. The following sections will provide a more in-depth discussion of the specifics of these technologies.

3.1.1. Radio frequency identification

RFID is an advanced technology that employs electromagnetic transmission and Radio Frequency (RF) compatible integrated circuits to store and retrieve data. An RFID system comprises essential components such as RFID readers, RFID tags, and the communication between them. RFID readers can read the data transmitted by RFID tags and enable bidirectional communication with the tags. This communication occurs through defined RF signals and protocols, allowing for the exchange of information between the readers and tags.

Passive tags and active tags represent the two primary categories of RFID tags. Passive RFID tags do not require batteries to operate; they extract energy from the RF signals emitted by the reader and transmit data back. These tags are mainly used as an alternative to traditional barcode technology and offer advantages such as small size and low cost. They add information by modulating the return signal and generally have a reading range of 1 to 2 m but are limited by their passive nature and relatively short reading distances. In contrast, active RFID tags have built-in batteries and can actively send signals, so they have a larger reading range and stronger signal transmission capabilities, but at a relatively high cost.

Despite not being the most accurate or the easiest IPS to implement, RFID has been extensively researched for its industrial applications. Our sample includes 86 studies on RFID positioning, encompassing 81 positioning systems solely based on RFID technology and 5 hybrid positioning systems incorporating RFID technology. Montaser et al. [36] employed RFID technology to facilitate cost-effective indoor location identification and material tracking within construction projects. Utilizing RFID technology to achieve target tracking has also proved useful in other studies [37,38]. Based on the target location, RFID is further studied for resource stock-taking [39], resource allocation [40–43], process control [44–46], real-time scheduling [47–50], bottleneck identification [51,51,52], staff states monitoring [53], collision prevention [54], and hazard detection [55].

For two-dimensional (2D) localization, Montaser et al. [36] utilized a triangulation method to identify user locations and track materials, achieving an average error of 1.0 m and 1.9 m, respectively. Notably, their proposed method demonstrates complete accuracy in detecting worker and material locations. For three-dimensional (3D) localization, Cai et al. [38] introduced a novel algorithm called BConTri, which integrates the boundary condition method and the three-coordinate concept to estimate the three-dimensional position of a tag in real-world coordinates. Experimental results indicate that the algorithm achieves a 3D position error of 1.43 m. In addition, several studies have improved the 3D position error by using various localization techniques. For example, Montaser et al. [36] conducted a comparative analysis of two localization techniques, namely triangulation and proximity. The findings of their study demonstrated that the triangulation method exhibits superior accuracy compared to the proximity technique.

Table 3
Comparisons of indoor positioning technologies.

Technology		Accuracy (m) [32,33]	Energy (mW/tag) [32,34]	Cost [14]	Scalability [34,35]
RFID	(Active)	~1–3	~250	Medium	Medium
	(Passive)	~0.15–0.5	<50	Low	High
BLE		~2–5	~25–50	Low	High
UWB		~0.15	~600	High	Low
Wi-Fi		~1.7	~100	Low	High
ZigBee		~2.77	~74.1–81	Low	High

3.1.2. Bluetooth low energy

The article identifies 33 articles related to BLE research, of which the articles that contain only the localization techniques of BLE technology are 30. BLE encompasses specifications for the physical and MAC layers, enabling the connectivity of various fixed or mobile wireless devices within a personal space. BLE signals are detected through BLE beacons, and the individual's location is determined by combining the RSSI with the location of the beacon. The BLE protocol incorporates in-phase and quadrature sampling techniques, enabling the calculation of angles of arrival and departure using BLE. One of the key advantages of BLE is its extremely low power consumption, typically around 0.367 mW. This enables battery-powered devices to operate for extended periods of time, often lasting for years without requiring battery replacement [10]. However, there are certain drawbacks associated with BLE. One of the disadvantages is the potential for interference, which can affect the reliable detection of BLE signals through the beacons used for their detection. Additionally, the reliability of detecting BLE signals may be compromised, posing challenges in certain scenarios.

The accuracy of BLE in industrial applications has also been studied. For example, Wu et al. [56] designed an indoor tracking algorithm called GITA to localize product carts via BLE and applied UWB to sample tagging during the training phase to achieve a localization accuracy of 2 m in industrial environments. Zhao et al. [57] developed a BLE-based multimodal bionic learning (MMBL) approach with a 95 % error within 3.41 m and remains effective after one year of use. Carrasco et al. [58] devised a system designed to locate the nearest machine to a user. This system collects the Received Signal Strength Indication (RSSI) data from low-cost BLE beacons installed on the machines and returns the name of the closest machine. The system achieves an approximate guessing rate of 89 % accuracy.

The main application of BLE in the industry is target tracking ([59–62]). Based on target tracking, other scholars have applied BLE to collision prevention. For example, Huang et al. [63] devised a methodology for detecting proximity areas and delivering proximity safety alerts to workers at construction sites. Their approach utilizes BLE and has undergone multiple tests on construction sites. The results demonstrated that the system effectively detects proximity and promptly generates vibrotactile alerts that are easily noticeable by the workers. Arslan et al. [64] used a data collection and trajectory preprocessing subsystem based on real-time BLE beacons to extract multifaceted trajectory characteristics and workers' stay areas and proposed a worker trajectory analysis system called WoTAS, which can help safety managers remotely monitor and control the construction activities in dynamic environments to understand the workers' activities and reduce the number of incidents on the construction sites.

3.1.3. Ultra-wideband

34 articles investigating ultra-wideband in industrial applications were identified, of which 28 were articles that included only UWB technology for localization. UWB is an especially appealing technology for indoor localization due to its inherent resistance to signal interference compared to other technologies. UWB signals possess a distinctive characteristic as they can penetrate various materials, including walls (although metals and liquids can interfere with UWB signals). Furthermore, the extremely short duration of UWB pulses aids in mitigating multipath distortion commonly encountered in indoor environments. This characteristic of UWB enables more precise and accurate

localization results [65].

Scholars have applied UWB to industry and evaluated its accuracy in different environments. Pease et al. [66] implemented a UWB system within an operational indoor industrial facility and showcased ranging accuracy that is on par with existing systems tested in non-industrial environments. Moreover, UWB has been successfully integrated with other technologies to enhance the accuracy of localization algorithms. For example, Wu et al. [56] developed a GITA based on a long and short-term memory network. This innovative algorithm integrates UWB and BLE technologies and was assessed through a real-world case study conducted at a prominent computer manufacturing company. Despite the presence of various types of noises in the manufacturing scenario, the GITA showed superiority over the existing methods with an accuracy of 98.12 %.

The applications of UWB technology span various industrial domains. One prominent area of application is target tracking, as evidenced by the extensive research conducted in this field ([67–69]). These studies have demonstrated the efficacy of UWB in accurately locating and monitoring the position of targets, making it a valuable tool for applications such as asset management, personnel tracking, and device monitoring. In addition to target tracking, scholars have also explored the application of UWB in the realm of security management. For example, Halawa et al. [70] combined UWB technology with a warehouse management system (WMS) and a forklift fleet management system (FFMS). They conducted an analysis of warehouse safety across seven dimensions, including factors such as braking roughness, adherence to routing strategies, driver behavior at intersections, congestion identification and prevention, speed control per zone, impact analysis, and failure analysis. The analysis was performed using relevant data to assess and improve warehouse safety. Maalek et al. [71] investigated the impact of variables such as speed and heading on the accuracy of estimating the location of dynamic tags. Their findings revealed an inverse relationship between accuracy and the speed of the tag, the number of tags being tracked, and the complexity of the tag's path of travel. Additionally, the researchers proposed a novel method for defining hazardous areas in construction sites, showcasing the effectiveness of UWB in locating dynamic resources and enhancing safety management within construction sites.

The application of UWB to production process control is also a research direction. For example, Xia et al. [72] introduced a novel mobile production monitoring system equipped with human-in-the-loop control. This system utilizes UWB and inertial measurement unit (IMU) fusion indoor localization technology to deliver precise indoor localization information for the production elements within a factory setting. The proposed system was implemented in a hydraulic cylinder factory, significantly reducing physical and mental fatigue among production personnel.

3.1.4. Wireless fidelity

The article identifies 8 articles related to Wi-Fi research, of which 6 articles include only Wi-Fi technology for localization. With the increasing prevalence of portable user devices, it is worth noting that many of these devices now come equipped with Wi-Fi capabilities. This widespread adoption of Wi-Fi technology renders it highly suitable for indoor localization purposes. Existing Wi-Fi access points can serve as valuable reference points for collecting signals in indoor localization systems [73]. It is possible to construct basic localization systems that can achieve reasonable positioning accuracy without the need for supplementary infrastructure. Nonetheless, conventional Wi-Fi networks are generally deployed for communication purposes, aiming to maximize data throughput and network coverage rather than for positioning objectives. Therefore, innovative and efficient algorithms are necessary to enhance the positioning accuracy of these networks.

Scholars research the accuracy of Wi-Fi when applied in industry. For example, Ma et al. [74] designed a module called enhanced magnetic fingerprinting-based indoor localization (MaLoc), which provides 2D localization services with an accuracy of 1 to 2.8 m. Budak et al. [75] compared four solutions, namely, UWB, Wi-Fi, ultra-high frequency (UHF) RFID, and active RFID, and the optimal system was determined to be the Wi-Fi real-time locating system. Studies have also integrated Wi-Fi with other technologies, such as magnetic fields [74] and IMU [76]. Exploring location-based services is also a research direction for Wi-Fi. For example, Falkowski et al. [77] explored the standard indoor positioning solutions required for location-based services and used Wi-Fi-based geofencing as an example to demonstrate the need for employing feature models for an efficient design process.

3.1.5. ZigBee

ZigBee, a wireless communication standard developed by the ZigBee Alliance, was devised with the specific objective of addressing the demand for cost-effective implementation of ultra-low-power and low-data-rate wireless networks. ZigBee builds upon the IEEE 802.15.4 standard, which focuses on the physical and MAC layers to facilitate the establishment of low-cost, low-data-rate, and energy-efficient personal area networks [78]. ZigBee standardizes the upper layers of the protocol stack, encompassing the network layer and the application layer. The network layer is responsible for organizing and enabling routing in multi-hop networks, while the application layer serves as a framework for facilitating distributed application development and communication.

Due to its low-cost and low-power characteristics, ZigBee has been utilized in the development of IPS. RSSI levels are easy to obtain because they are included in each packet without additional hardware. ZigBee-based IPS typically comprise sensor networks and wireless sensor network algorithms. These systems commonly employ algorithms that utilize RSSI values to estimate the location. Consequently, they rely on similar techniques as Wi-Fi and BLE, such as fingerprinting and propagation models. While ZigBee is advantageous for localizing sensors in wireless sensor networks, it poses challenges when it comes to its usability on most user devices. As a result, it is not well-suited for indoor localization of users [11].

Several scholars conduct research related to ZigBee. Zhao et al. [79] developed a comprehensive warehouse environment monitoring system using ZigBee technology. The system adopts a tree-like network topology comprising a ZigBee coordinator, multiple ZigBee routing nodes, and end devices. Additionally, they established an evaluation model based on activity-based costing to assess the level of warehouse logistics costs and analyzed the various factors influencing warehouse logistics costs. Cui et al. [80] introduced a ZigBee-based fingerprint positioning method for locating railroad tunnel staff. They proposed an improved K-means algorithm to cluster the location fingerprinting database, aiming to reduce the number of matches between online stages and reference nodes. This approach facilitated online positioning, enabling managers to accurately determine the location of tunnel staff in a timely manner. As a result, it facilitated the efficient deployment of staff and the effective utilization of fingerprinting techniques. Mardeni et al. [81] devised a tracking and localization system for mobile asset tracking and localization, leveraging ZigBee technology, RSSI, and the trilateral measurement method. This system was designed to be straightforward, cost-effective, and dependable, providing a solution for accurately tracking and localizing mobile assets.

3.2. Techniques

This study categorizes indoor positioning techniques into three broad classes: signal-based, angle-based, and time-based methods. Recognizing that the performance of a given indoor positioning technique can vary across different environments, Table 4 provides a comparative overview of the characteristics of some commonly employed localization techniques for reference. The subsequent sections will introduce the distinctive characteristics, as well as the advantages and disadvantages, of each type of indoor positioning technique.

Table 4
Comparisons of indoor positioning techniques.

Techniques	Technology	Computation	Latency	Synchronization
RSSI	BLE	Low	Hard real-time	No
AoA	BLE 5.1	High	Soft real-time	No
ToA	UWB	Medium	Hard real-time	Yes
TDoA	UWB	Medium	Hard real-time	Yes

3.2.1. Signal-based techniques

The approach based on received signal strength (RSS) is considered one of the simplest and extensively employed methods for indoor localization [82]. RSS refers to the actual strength of the received signal, typically measured in decibels milliwatts (dBm) or milliwatts (mW). It serves as a means to estimate the distance between the transmitter (Tx) and receiver (Rx) devices. A higher RSS value indicates a shorter distance between the Tx and Rx. When the transmitted power or the power at the reference point is known, various signal path loss propagation models can be employed to estimate the absolute distance. It's important to note that RSSI, often confused with RSS, is a relative measure of RSS and is characterized by arbitrary units defined by individual chip vendors. For instance, Atheros Wi-Fi chipsets employ RSSI values ranging from 0 to 60, whereas Cisco adopts a range between 0 and 100.

Multiple formulas have been developed to calculate distance using RSSI, establishing a relationship between signal power and distance. The widely used formula is the log-normal path loss, which represents a general form of the Friesian equation. Using RSSI and a straightforward path loss propagation model [83], the distance d between Tx and Rx can be estimated from

$$RSSI = -10n\log_{10}(d) + A \tag{1}$$

where n is the path loss exponent, and A is the RSSI value at the reference distance from the receiver. RSSI can be applied to trilateral measurements, fingerprinting, and proximity methods. Trilateral measurement methods leverage RSSI to estimate the distance between a reference node and a mobile node, enabling the determination of object locations associated with the reference node. Proximity-based methods utilize RSSI values to establish geofences, which detect when an object enters the vicinity of the geofenced area. Fingerprinting applies RSSI measurements to obtain features for each point on the map [84].

Fingerprinting methods are based on RSSI. The method is comprised of two distinct phases, namely offline and online. During the offline phase, the received RSSI signals are utilized to map all areas and stored in a database. In the online phase, the RSSI values measured in real-time are compared against the predefined values within the database, allowing for the identification of the closest point in the vicinity. Subsequently, the current position is mapped to the predefined points on the map.

Although RSS-based methods are simple and cost-effective, they often have limited localization accuracy, particularly in non-line-of-sight scenarios. This reduced accuracy can be attributed to additional signal attenuation caused by obstacles such as walls, multipath fading, and indoor noise, leading to significant fluctuations in RSS values. To address these challenges, various filtering techniques and averaging mechanisms can be employed to mitigate the effects of signal fluctuations. However, achieving high localization accuracy without using complex algorithms is unlikely.

3.2.2. Angle-based techniques

As shown in Fig. 3, AoA-based methods utilize an antenna array on the receiver side to estimate the angle at which the transmitted signal reaches the receiver. This is achieved by utilizing and calculating the difference in arrival times of individual elements of the antenna array and determining the intersection of multiple orientations based on the angle of the received signal.

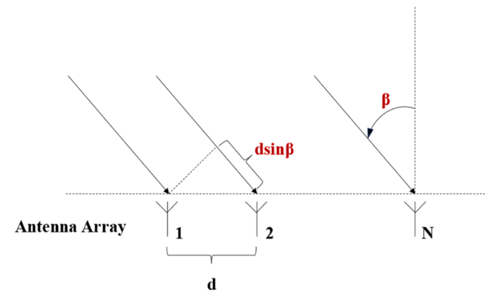

Fig. 3. AoA-based localization.

The advantage of AoA-based techniques is that they do not require time synchronization and can provide an accurate estimation of the transmitter-receiver distance when the distance is relatively short. In a 2D environment, the device/user position can be estimated using two anchor nodes, while three anchor nodes are required for a 3D environment.

However, this method necessitates defining the positions of the anchor nodes, which must be equipped with directional antennas. This requirement can increase the overall cost of the system. Indeed, AoA-based techniques typically demand more complex hardware and meticulous calibration compared to RSS techniques. The accuracy of AoA estimation tends to decrease as the distance between the transmitter and receiver increases. This is because even a small error in the angle of arrival calculation can result in a significant error in the actual position estimation [73]. Moreover, acquiring the line-of-sight component of the approach angle proves challenging in indoor settings due to the presence of multipath phenomena. UWB emerges as a pivotal technology for achieving accurate positioning through the utilization of the angle of approach method. Recently, Bluetooth 5.1 has made notable advancements in positioning services by incorporating improved techniques such as AoA and Angle of Departure (AoD) [85].

3.2.3. Time-based techniques

Time of Flight (ToF) or ToA methods utilize the propagation time of a signal to calculate the distance between a transmitter (Tx) and a receiver (Rx). This is achieved by multiplying the ToF value by the speed of light ($c = 3 \times 10^8$m/s) to obtain the physical distance between Tx and Rx. In Fig. 4, the ToF data obtained from three reference nodes is employed to estimate the distance between the reference node and the device. By leveraging the underlying geometry, it becomes possible to calculate the position of the device in relation to the access point. It's worth noting that ToF requires precise synchronization between the transmitter and receiver, and in many cases, a timestamp needs to be transmitted along with the signal, depending on the underlying communication protocol.

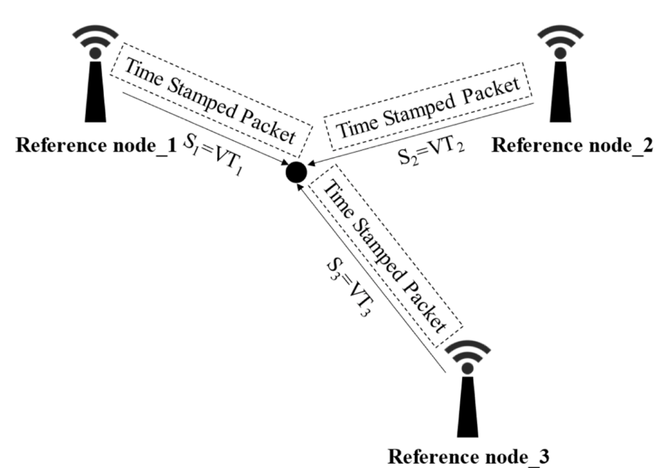

Fig. 4. ToF-based localization.

The accuracy of Time of Flight (ToF) is influenced by two crucial factors: signal bandwidth and sampling rate. A lower sampling rate in time results in reduced ToF resolution since the signal may arrive between sample intervals. In multipath indoor environments, a larger bandwidth leads to a higher resolution when estimating ToF. While employing a larger bandwidth and super-resolution techniques can enhance ToF performance, they do not entirely eliminate substantial localization errors in scenarios where there is no direct line-of-sight path between the transmitter and receiver. This is because obstacles deflect the transmitted signal, causing it to traverse a longer path, consequently increasing the propagation time from Tx to Rx.

Let t_1 be the time when Tx i sends a message to Rx j and receives it at t_2, where $t_2 = t_1 + t_p$ (t_p is the time required for the signal to propagate from Tx to Rx). Therefore, the distance between i and j can be calculated using Eq. (2)

$$Dij = (t2 - t1) \times v \tag{2}$$

where v is the signal speed.

TDoA is a technique that leverages the difference in signal propagation times from multiple transmitters as measured at the receiver. Unlike ToF which utilizes absolute signal propagation times, TDoA focuses on the relative differences in arrival times. The TDoA measurements are converted to physical distance values. To compute the exact position of the receiver, TDoA measurements from at least three transmitters are necessary, as the receiver's position corresponds to the intersection of three or more hyperbolic surfaces. Solving the hyperbolic system of equations can be achieved through methods such as linear regression or linearizing the equations using a Taylor series expansion. Similar to ToF, the accuracy of TDoA estimation depends on factors such as signal bandwidth, the sampling rate of the receivers, and the presence or absence of a direct line of sight between the transmitters and receivers. TDoA only requires synchronization between the transmitters.

Ranging Time of Flight (RToF) is a technique that measures the round-trip signal propagation time between a transmitter (Tx) and a receiver (Rx) to estimate the distance between them. Similar to ToF, RToF relies on the measurement of signal propagation time, but it involves the complete round trip from the transmitter to the receiver and back. RToF offers an advantage over ToF in terms of clock synchronization requirements between the Tx and Rx. The synchronization needed for RToF is relatively modest compared to the precise synchronization required for ToF. However, the accuracy of RToF estimation is affected by factors like ToF, such as the sampling rate and signal bandwidth. In the case of RToF, these factors have a greater impact because the signal is sent and received twice. Another essential consideration for RToF-based systems is the receiver response latency. This latency is influenced by the receiver electronics and any protocol overhead. Minimizing the receiver response latency is crucial to achieve accurate RToF measurements.

3.2.4. Integration with machine learning

Machine learning is a technique and methodology in artificial intelligence that enables computer systems to learn and improve automatically without explicit programming instructions by utilizing large amounts of data and statistical principles. The fundamental concept behind machine learning is to enable intelligent decision-making and behaviors by extracting patterns and regularities from data, enabling the performance of tasks such as prediction, classification, and clustering. The proliferation of data and advancements in computing power have contributed to the significant rise of machine learning in recent years. It has been widely used in many fields, such as construction, logistics, and manufacturing [86–88], and has achieved remarkable results.

Machine learning can effectively improve the performance of IPS. First, machine learning can utilize a large amount of data for feature extraction, and it can automatically learn and discover patterns and regularities in the data to extract useful features related to indoor positioning. This automated feature extraction process is more efficient and accurate than manually designed feature extraction methods. Second, machine learning models have nonlinear entity modeling capabilities to better capture complex relationships and nonlinear features in IPS. This enables machine learning to predict and localize positions more accurately, improving the precision and accuracy of the positioning system. In addition, machine learning is a data-driven approach that improves the adaptability and generalization of IPS through learning and optimization of large-scale data. Machine learning models can learn from data in multiple dimensions and from multiple sensors to model different environments and scenarios, thus providing more robust localization results. The machine learning techniques commonly used in IPS are described next.

In Support Vector Machine (SVM), each data point in a dataset is represented as a point in an N-dimensional space, where N corresponds to the number of features. The SVM algorithm aims to identify a hyperplane or a set of hyperplanes that effectively separate different data classes by defining boundaries in this N-dimensional space. SVM can be utilized for localization tasks by leveraging both offline and online RSSI measurements [35]. These measurements can be used as features in the SVM algorithm to train a model that can accurately estimate the location of a target in a given environment. The trained SVM model can then be employed for online localization, where real-time RSSI measurements are used as input to predict the target's position. Rezgui et al. [89] introduced a novel approach called the normalized rank classifier (NR-SVM) based on support vector machines (SVM). This method was specifically designed to address hardware variations and signal fluctuations encountered in Wi-Fi fingerprint-based localization. The proposed approach prioritizes the main features and considers the dimensionality of the feature vectors. Through experimental evaluations, the researchers demonstrated the robustness and effectiveness of the NR-SVM method in tackling the challenges associated with Wi-Fi fingerprint-based localization. Chriki et al. [90] skillfully combine SVM with RSSI to convert the problem of determining the precise location of a target into the problem of determining the region where the target location is located and to solve the problem that it is difficult to locate the target based on the RSSI measurements alone correctly.

K Nearest Neighbors (KNN) is a nonparametric machine learning algorithm used for classification and regression tasks. It does not make any assumptions about the underlying data distribution. The core principle of KNN is to determine the class of a test point by considering the majority vote of its K nearest neighbors, represented as a feature vector. The KNN algorithm is simple to implement and relies on two key parameters: the value of K (number of neighbors) and a distance function (such as Euclidean, Minkowski, or Manhattan). However, as the dataset size increases, the computational time required to calculate distances between new and existing data points also grows. Consequently, the performance of KNN can degrade rapidly with larger datasets. Additionally, data imbalance issues can pose challenges for KNN, as the majority class may dominate the decision-making process, leading to biased results. Akré et al. [91] employed an ensemble function that incorporates the RSSI values from all potential RFID readers that receive passive RFID signals. They proposed a location feature and compared it with other tags situated in known locations within the proximity. To enhance the accuracy of localization, they utilized a KNN algorithm-based approach to estimate the location of the target tag. This approach aimed to improve the precision of localization in their study. Kriz et al. [92] used BLE beacons and RSS of Wi-Fi and used weighted KNN to estimate the unknown location.

An Artificial Neural Network (ANN) is a computational system that is composed of interconnected nodes known as neurons. These neurons are linked together with weighted connections. An ANN typically comprises an input layer, an output layer, and one or more hidden layers in between. During the training process of an ANN, input data is passed through the network, and the output is compared to the desired output using a loss function. The network then backpropagates the error, updating the connections' weights to minimize the loss. This adjustment of weights based on the backpropagation of errors allows the network to learn and improve its performance over time. The aim is to efficiently optimize the weights to make accurate predictions or classifications based on the given input data. Adege et al. [93] employed an ANN with the backpropagation algorithm to address a regression problem and enhance the accuracy of a localization system. Their experimentation demonstrated that the localization system achieved an accuracy of 50 % for errors less than 0.5 m and 100 % for errors less than 0.9 m. This indicates that the ANN-based approach significantly improved the precision of the localization system and yielded favorable results in their evaluation. Anand et al. [94] investigated the application of ANN to enhance the accuracy of RSSI localization algorithms. They leveraged the parallel computation capabilities and non-linear characteristics of neural networks to improve the performance of localization. Their experiments and analysis demonstrated that the utilization of ANN significantly improved the localization performance.

An autoencoder is a type of unsupervised neural network architecture in which the target output is set to be the same as the input. The primary objective of an autoencoder is to reconstruct its input data at the output layer. It consists of an encoder network that maps the input data to a lower-dimensional latent space representation, and a decoder network that reconstructs the input data from the latent space representation. Autoencoders can be trained to learn compressed and robust representations of the input data by constraining the network with a limited number of neurons in the hidden layers. By doing so, the autoencoder is forced to capture the most salient features of the input data in a compact form. This compressed representation can be used for various purposes, such as data compression, denoising, or anomaly detection. Wang et al. [95] developed a feature extraction technique utilizing a stacked denoising autoencoder. The experimental findings demonstrate the efficacy of the proposed approach in addressing the temporal variations and sparsity inherent in Wi-Fi signals during the localization procedure. Zhang et al. [96] introduced a feature extraction algorithm named joint multi-task stacked denoising auto-encoder. This method was devised to tackle the instability of Wi-Fi signals and the high-dimensional sparsity observed in fingerprint data, with the objective of enhancing the performance of IPS based on Wi-Fi technology.

3.3. IPS assessment evaluation

This section introduces the evaluation of IPS, which is distinct from the assessment of individual technologies. Evaluating an IPS for industrial environments primarily involves considering four key factors: cost, accuracy, robustness, and scalability. These factors must be tailored to the specific needs of each application.

3.3.1. Cost

When evaluating the overall cost of an IPS, a multifaceted approach is required, considering both monetary and non-monetary factors. On the monetary side, the costs associated with such systems can encompass a range of elements, including the acquisition of hardware equipment, software development and licensing fees, as well as the expenses incurred during system deployment and ongoing maintenance. However, the assessment of IPS's cost goes beyond mere financial considerations. A number of non-monetary factors must be considered to arrive at a comprehensive understanding of the true cost implications.

Time costs are an essential consideration. The time required to install, configure, and calibrate the positioning equipment and the ongoing time investment needed to maintain and update the system must be accounted for. Time costs also encompass the project management and coordination efforts, as deploying an indoor positioning system typically requires communication and collaboration with multiple stakeholders, such as the owner, IT department, and construction team. These time-related factors can impact the project plan and implementation schedule.

Space cost is another factor to weigh. The physical space required for the equipment and the limitations of the equipment layout, as well as any necessary modifications to the building, must be considered. Positioning technologies with a smaller footprint and that are easier to install should be preferred. Consideration should also be given to utilizing existing infrastructure, such as communication cables and power systems, to reduce the need for new investments. The planning, implementation, and monitoring of the IPS require specialized knowledge and expertise, both during the initial design stages and for ongoing troubleshooting and technical support. Selecting a straightforward system can help minimize the labour costs associated with operation and maintenance.

Human resource costs are also an important consideration. The planning, implementation, and monitoring of IPS require human resources. This includes the specialized knowledge and experience required during the planning and design stages of the system, as well as the effort and expertise required for troubleshooting and technical support. Choosing a system that is easy to maintain can reduce the cost of operation and maintenance labour.

Energy cost is another crucial factor. The power requirements of the indoor positioning devices, including both electricity and battery power, must be carefully evaluated. Passive energy devices that rely on ambient energy sources may offer lower energy costs. Additionally, the input requirements for the power supply infrastructure should be considered, and alternative power supply options, such as decentralized or renewable energy, can be explored to reduce energy costs. Effective energy consumption management is also essential to optimize the use of energy resources.

By considering these comprehensive factors like monetary costs, time, space, human resources, and energy, organizations can conduct a more thorough assessment and make informed decisions when developing and deploying IPS. This holistic approach helps ensure that the selected system aligns with the organization's needs and desired goals while also addressing sustainability concerns.

3.3.2. Accuracy

Accuracy is the most core index in the design of IPS. It directly determines the accuracy of the positioning results, thus affecting the performance and application value of the whole system. Usually, accuracy is evaluated by measuring the average distance error between the estimated position and the actual position. Higher accuracy means that the positioning result is closer to the actual position, which is crucial for many industrial application scenarios. However, companies often need to trade-off between accuracy and other system characteristics in pursuit of high accuracy.

Firstly, improving accuracy often requires increasing the number and density of localization devices or using more complex algorithms and techniques, which can significantly increase system cost, complexity, and energy consumption. In an industrial environment, these factors are often a significant concern. Therefore, companies must weigh accuracy against system cost, complexity, energy consumption, and feasibility of implementation and maintenance to find an optimal balance.

Secondly, the characteristics of the industrial environment itself can have a significant impact on positioning accuracy. Compared with ordinary indoor environments, factories, warehouses, and other industrial sites are usually full of metal equipment, pipelines, and sources of electromagnetic interference. These factors will seriously affect the wireless signal-based positioning technology, reducing the positioning accuracy. Therefore, when choosing positioning technology, we need to fully consider the environmental characteristics and take corresponding optimization measures, such as choosing the technology solution with strong anti-interference ability, optimizing the antenna layout, enhancing the signal processing algorithms, etc., to improve the positioning accuracy in the industrial environment.

In addition, different industrial application scenarios may have different requirements for positioning accuracy. Higher positioning accuracy may be the key in some scenarios requiring fine material management, such as automatic robot pickup or unmanned automatic guided vehicle handling. However, in some scenarios of personnel localization or large-scale item tracking, relatively low accuracy requirements may be sufficient to meet the needs. Therefore, the system design should fully consider the specific application requirements and dynamically adjust the accuracy target and system configuration to maximize the satisfaction of the needs in different scenarios.

Finally, in the actual deployment process, it is essential to conduct field tests and performance verification to assess the real-world positioning accuracy of the indoor positioning system within the specific industrial environment. This empirical evaluation allows for the continuous optimization of system parameters and deployment schemes based on the insights gained from the feedback. Only in this way can we ensure that the indoor positioning system really plays its due value in industrial scenarios.

In conclusion, accuracy is a complex multi-factor problem when applying indoor positioning technology in industrial environments. In the design and deployment of IPS for industrial applications, a comprehensive evaluation and optimization process is essential to strike the optimal balance between performance, cost, and complexity. This holistic approach must consider a range of technical characteristics, environmental conditions, application requirements, and other relevant factors. Only in this way can indoor positioning technology play its due role in the industrial field.

3.3.3. Robustness

The application of indoor localization techniques in industrial scenarios requires a high degree of robustness. Factory environments usually face challenges that can seriously affect the localization system's performance, so improving the robustness of indoor positioning techniques is crucial.

Firstly, signal occlusion and multipath propagation problems that are common in industrial environments can lead to significant deviations in measurements. For example, machinery, metal structures, and human activities can cause signal interference and dramatic fluctuations in signal strength. To cope with this situation, several measures are needed to improve the robustness of the positioning system. First, in addition to utilizing standard technologies such as Wi-Fi, BLE, and inertial sensors, other positioning technologies such as RFID, UWB, and ultrasonic can be considered for integration to fully utilize the advantages of sensors with different physical principles. Multi-sensor fusion can improve the system's ability to tolerate the failure of a single sensor and enhance the overall reliability. At the same time, the advantages of different sensors complement each other, which is conducive to improving the positioning accuracy in complex industrial environments. In addition, it can be combined with machine vision, industrial cameras, and other visual sensors to further enhance the robustness of positioning by utilizing the rich environmental information.

Secondly, due to the harsh conditions in industrial environments, such as temperature, humidity, dust, etc., wireless signals are susceptible to solid interference and attenuation, which may also cause performance degradation or even damage to the sensors themselves. This requires the positioning system to have the ability of self-diagnosis and fault tolerance, and to be able to make real-time adjustments for the dynamic signal environment. This includes adaptive filtering, gain control, spectrum analysis, and other techniques to improve the suppression of noise and interference. The system should be able to detect abnormal states of sensors and automatically adjust algorithm parameters or switch to alternate sensors to ensure that reliable localization results are still provided when some sensors fail. At the same time, machine learning technology can be used to continuously optimize the signal processing algorithm through training and online learning to adapt to the characteristics of different industrial scenarios.

Again, the design of positioning algorithms should also take into full consideration of various abnormal situations, such as sensor failure, data loss, measurement deviation, etc., and have the corresponding fault-tolerant mechanism. For example, robust geometric localization algorithms, probabilistic statistical models, Bayesian filtering, etc., can be used to improve the anti-jamming ability of outliers and missing data. At the same time, fault diagnosis and fault tolerance mechanisms can be introduced to quickly identify and isolate faulty sensors to maximize the use of adequate data to complete the positioning.

In addition, the dynamic changes in the industrial site also pose a challenge to the robustness of the indoor positioning system. The movement of equipment, the adjustment of process flow, and the change of environment layout may lead to the failure of the localization model and parameters. Therefore, the design of localization algorithms should consider the dynamic environment adaptability and be able to use online learning or incremental updating methods to automatically adjust the model to adapt to environmental changes to ensure long-term stable operation.

In conclusion, high robustness is an essential requirement when applying indoor positioning technology in industrial scenarios. Through the integration of multi-sensor fusion, fault tolerance mechanism, and dynamic environment adaptability, the performance and reliability of IPS can be significantly improved to meet the needs of practical applications in complex industrial environments. The ideal IPS should possess the capacity for dynamic configuration and self-healing capabilities. Such a system must have the inherent ability to independently adjust its deployment scheme and parameter configurations in response to environmental changes, thereby maximizing the continuity and reliability of the positioning service.

3.3.4. Scalability

Scalability is a crucial consideration when deploying IPS in industrial environments. A critical aspect of scalability in IPS is the ability to maintain stable and reliable localization performance as the operational range expands and new devices or nodes are introduced into the system. The main factors affecting the scalability of IPS include the positioning range, signal transmission and data processing, and the dimensional space of the industrial environment.

Positioning range is the primary consideration for scalability. Industrial environments are typically large, and systems need to support a wider spatial range as positioning coverage is progressively expanded. However, a positioning range that is too large may lead to a degradation of positioning performance, and signal attenuation and occlusion problems will become more serious. Therefore, when expanding the positioning range, the system must take corresponding technical measures to ensure the accuracy and stability of positioning. This may involve increasing the density of positioning nodes, optimizing the antenna layout, adopting higher sensitivity receiving equipment, etc.

Signal transmission and data processing capabilities are also vital to scalability. With the expansion of the positioning range and the increase in the number of device nodes, the system needs to process a large amount of real-time positioning data. This places higher demands on the bandwidth and latency of the communication network as well as the computational performance of the central server. If the underlying hardware and network infrastructure cannot support the efficient transmission and processing of massive data, the scalability of the system will be seriously constrained. Therefore, it is necessary to adopt high-performance computing platforms and communication solutions and optimize the collection, transmission, and analysis processes of positioning data to ensure that the system maintains good real-time responsiveness in the expansion process.

The dimensional space of the industrial environment is also an essential factor affecting scalability. This spatial complexity poses unique challenges for the effective deployment and utilization of IPS in these settings. The three-dimensional nature of many industrial and logistical facilities, with the presence of multi-level structures and varied obstructions, can significantly impact the performance and accuracy of traditional IPS technologies, which were primarily designed for planar environments. For different dimensions of the space characteristics, the positioning system needs to use suitable technical solutions, such as combining inertial navigation, ultra-wideband, RFID, and other technologies, and reasonable planning for the deployment of equipment. Only by fully considering the needs of the spatial dimension can we ensure that the scalability can be effectively utilized in different industrial environments.

To maintain the scalability of the indoor positioning system in industrial environments, it is necessary to take corresponding measures from several aspects. Firstly, the system should adopt a modularized design architecture. By making each functional module relatively independent, it is easy to add new positioning nodes and devices flexibly according to the demand. This modular design not only improves the flexibility and adaptability of the system but also facilitates future maintenance and upgrading, thus ensuring overall scalability. Secondly, choosing a high-performance hardware platform is also the key to ensure scalability. The hardware platform includes the use of a powerful central processing unit, high-capacity storage and memory, and a high-bandwidth network interface. Only with sufficient computing and communication capabilities the system can maintain good real-time responsiveness when increasing the number of device nodes and processing a large amount of positioning data. In addition, the use of dynamic positioning algorithms and signal transmission techniques is also essential. To cope with the changes in different environmental conditions, the system should adopt adaptive positioning algorithms and use machine learning and other methods to dynamically optimize the algorithm parameters. At the same time, the use of advanced wireless communication technologies such as self-organizing network and frequency hopping can improve the system's anti-interference ability and transmission stability. The application of these dynamic technologies helps to ensure that the positioning performance maintains a high level during the expansion process. Finally, before the system is deployed, comprehensive scalability and stress tests are required. This includes testing the system's performance metrics at different scales and evaluating its stability during gradual expansion. The system can simulate large-scale operations through stress testing and other means to identify potential bottlenecks and weaknesses. Based on the test results, the system design is optimized to ensure that it can meet future changes in business requirements.

In summary, to realize the scalability of IPS, it is necessary to start from multiple angles, including the modular design, selection of high-performance hardware, use of dynamic technology, and system testing. Only through these comprehensive measures can it be ensured that the positioning system can be continuously and stably scaled up with changes in the industrial environment.

3.4. Summary

Overall, the surveyed articles show that researchers in industrial applications have so far reacted quickly to the newly introduced IPSs, which in addition to the five selected technologies contain several new IPS application concepts, such as IMU [37,72], magnetic fields [74], and location-based services [77].

This section summarizes the findings by technology. While RFID has attracted great interest in the last decade, positioning technologies such as BLE, UWB, Wi-Fi, and ZigBee in industrial applications have not yet been fully studied or reported. The status of the positioning systems that have been applied in the industry will be discussed in the next section.

4. IPS applications in Industry 4.0

As shown in Fig. 5, the number of articles examining the application of IPS in the context of Industry 4.0 shows an increasing trend with the number of years between 2014 and 2023. In this case, the number of articles is the same for 2018 and 2019.

As shown in Table 5, about 64 % of the articles examined the use of IPS in manufacturing, and about the same number of articles employed the use of IPS in logistics and construction, each accounting for about 18 % of the articles. Most of the IPS research focused on resource management (49 %) and production management (39 %), with a small number of studies focusing on safety management (12 %).

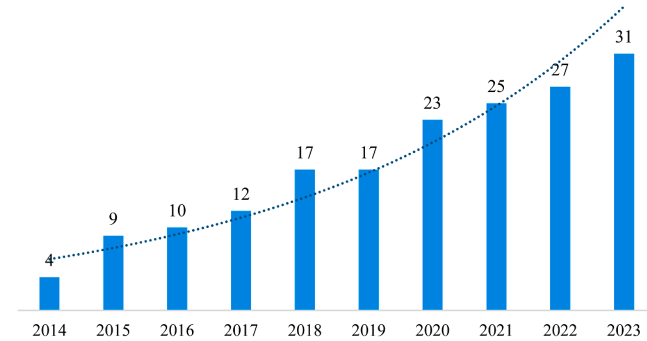

Fig. 5. Reviewed articles classification by years.

Table 5
Reviewed articles classification by applications in different fields.

Real-time decision-making	Manufacturing	Construction	Logistics	Total
Resource management	**59**	**7**	20	**86**
Object tracking	28	5	16	49
Resource allocation	21	1	2	24
Resource stock-taking	10	1	2	13
Production management	**48**	**10**	**10**	**68**
Bottleneck identification	11	1	2	14
Process control	22	8	6	36
Real-time scheduling	15	1	2	18
Safety management	**2**	**14**	**5**	**21**
Collision prevention	1	3	–	4
Hazard detection	1	5	2	8
Staff states monitoring	–	6	3	9
Total	**109**	**31**	**35**	**175**

4.1. Resource management

4.1.1. Object tracking

Real-time target tracking is the most popular direction of IPS research in manufacturing. Many studies have focused on applying IPS to record real-time location information of various types of production factors in industrial applications, e.g., finished product [44,58,73,97,98,83], work-in-process (WIP) [84], assets [85], components [39], and workers [67]. Based on the object of capturing spatial-temporal information of manufacturing resources, some studies proposed technical frameworks for applying IPS in the manufacturing industry for tracking various types of manufacturing factors in industrial scenarios. Several studies have utilized indoor positioning techniques for logistics operations tools and used goods recovery [99]. All kinds of production resources are visualized and traceable through IPS, laying a solid foundation for further object-based local optimization and global collaboration. Besides, the effectiveness of indoor positioning applications has also been the focus of research on IPS for commodity tracking. For example, Schroeer et al. [100] evaluate channel effects and impact on location accuracy in multipath and non-line-of-sight scenarios to improve the localization accuracy of UWBs in industrial environments. Beliatis et al. [101] compare different technologies and analyze their advantages and disadvantages to identify suitable technology solutions for product traceability in the metal manufacturing industry. solutions. Barbieri et al. [68] investigate the application of UWB in factory environments and propose an enhancement technique to mitigate the signal impairments that occur in this complex scenario.

Some studies conduct construction site tracking of moving targets.

Wong et al. [76] developed a localization module including inertial sensing data, Wi-Fi signal, and barometer unit integration to achieve cross-floor location tracking, tracking the location of moving people promptly, and sharing the localization results with the relevant participants. Cai et al. [38] proposed BConTri, which combines the "boundary condition method" and the concept of trilateration, to estimate the locations of tags in 3D real-world coordinates with GPS-equipped RFID readers. Montaser et al. [36] proposed a low-cost indoor location method using UHF RFID to track materials for construction projects. The proposed method can accurately detect the area of worker and material locations, and the results show that the average errors of this method are 1.0 m and 1.9 m, respectively.

Target tracking is also a research topic in the field of intelligent logistics. Hayward et al. [37] developed a low-cost, non-invasive method using passive RFID tags. In cases where magnetometers and zero-velocity updates cannot be used, drift is corrected by confirming the reference position to map the route taken by assets carried by personnel in indoor environments. A study [102] also explores the use of IPS systems to increase supply chain visibility to reduce costs, improve efficiency, prevent losses, and obtain competitive levels of customer satisfaction. The decision-making approach for selecting the most appropriate positioning technology is discussed in [75].

4.1.2. Resource stock-taking

In the manufacturing field, some studies [17,86] focusing on the framework of tracking services for manufacturing elements have compared the available methods to determine the applicability of tracking assets in indoor environments. In addition, some scholars have conducted inventory counting studies for different types of manufacturing resources. Kirch et al. [103] define smart logistics zones based on RFID, thus realizing the automatic identification and localization of logistics objects and applying them to pallet management. Giordano et al. [104] present an innovative device for continuously evaluating the usage of handheld power tools and detecting construction tasks as well as potential misuse through an energy-efficient architectural design. Pichler et al. [105] describe standardizing the design and use of self-sufficient mobile workstations and utilizing IPS to provide up-to-date locations to maximize the functionality and versatility of individual mobile stations and the entire plant environment. There are also studies focusing on plant metal parts [39], generating product storage [106], raw material tracking [62], and asset tracking [66].

Some researchers are also applying IPS resource stock-taking to construction and warehousing. Ma et al. [74] designed an enhanced MaLoc that integrates magnetic field and Wi-Fi technologies to obtain the real-time location information of personnel and facilitate personnel to locate and inspect neighboring building elements to ensure a more effective and collaborative construction quality management process. Xu et al. [107] proposed an intelligent management system to monitor the quantity of goods in a small-scale warehouse. This system collects and analyzes location data and real-time feedback information according to the relationship between goods quantity and digital signals. Mostafa et al. [108] proposed a new RFID-based warehouse management approach that enables the connection of multiple objects. This approach can help provide spatial-temporal visibility of all items in the warehouse, increasing efficiency and preventing inventory counterfeiting.

4.1.3. Resource allocation

Manufacturing resource allocation has also been the focus of research [109,106,110,52,111]. Effective resource allocation can provide the efficiency of enterprise resource utilization, reduce enterprise production costs, and thus improve enterprise competitiveness. Wang et al. [112] presented an active material handling method that applies cyber-physical systems technology on the shop floor. This method aims to make manufacturing resources like machines and carts intelligent so that they can sense, act, interact, and behave. Based on intelligent resources, they proposed a multivariate linear regression method that considered time weighting to predict the remaining processing time for the WIP. The method innovatively transforms the material handling strategy from a traditional reactive mode to an intelligent and proactive mode, which optimizes the allocation of smart trolleys, reduces the total non-value-added energy consumption of manufacturing resources, and optimizes the routing of smart trolleys. Zhao et al. [113] established a dynamic spatial-temporal knowledge graph model to represent digital twin copies with spatial-temporal consistency, and then performed relational reasoning based on task information of production logistics. A directed weighted graph algorithm is introduced to solve the production logistics resource allocation problem, which provides a new idea for solving the spatial disorder and temporal asynchrony problem of production resources. Lee et al. [43] proposed an intelligent system to realize data-driven resource allocation. The system consists of product material, people, information, control, and productivity functions with the aim of providing effective and timely support for enterprise resource allocation decisions. RFID is introduced to validate the effectiveness of allocation decisions. By refining the rules for RFID-collected data, resource allocation results are better adapted to the production situation. Wu et al. [56] designed a system architecture utilizing IPS to achieve spatial-temporal traceability and visibility of finished goods logistics on the factory floor and seamless cyber-physical synchronization. Production decisions are made with the help of spatial-temporal data, thus contributing to operational efficiency.

Several resource allocation-related studies focused on logistics and construction. Some studies related to resource allocation focus on logistics and buildings. Dzeng et al. [114] utilized RFID technology to track occupants and record movement data so as to design a model for the optimization of function-space assignment. Trab et al. [115] defined a negotiation mechanism for achieving sustainability that relies on Internet of Things (IoT) infrastructures and multi-agent systems to achieve optimal placement of products and people in a sustainable system and ensure safe product allocation operations. Trebuňa et al. [116] describe a step-by-step process for implementing a localization system that analyzes the movement of people, materials, and various tools to optimize the material flow and create virtual safety zones.

4.2. Production management

4.2.1. Process control

Many studies [112,96,37] carry out process control of manufacturing based on spatial-temporal information of objects. Zhong et al. [117] use production logic and timestamps to concatenate RFID data and propose an RFID-based cuboid model to interpret the information. In the real case study, the practicability of the proposed model is demonstrated and verified, which helps to simplify the daily operations of different end users. Guo et al. [118] designed a platform called a digital twin-enabled graduation intelligent manufacturing system for fixed-position assembly islands by integrating positioning technology with other technologies. The overall platform is divided into physical, digital, and service layers. Real-time integration and synchronization between the different layers guarantee that the resources are allocated accurately and used for suitable activities at the right time. Managers are eager to make decisions, and field workers can conduct duties efficiently. Wu et al. [29] developed a location-based logistics platform to track finished goods, by which location-based operation is activated to improve operational efficiency. The platform is validated in a real case. Overall productivity has also increased, with significant reductions in product pickup and emergency order inspection times, shorter order lead times, and improved service levels.

The process control function of IPS in the construction domain has also been studied by scholars. Ding et al. [119] described the graduation intelligent manufacturing system, which utilizes IoT-enabled prefabricated production for real-time spatial-temporal visibility and traceability and develops a multistage self-adaptive decision-making mechanism to improve the performance level of planning, scheduling, and execution in the presence of fluctuating runtimes. The proposed platform results in more than 70 % reduction in delayed operations compared to the traditional approach, and the mold table Idle time was reduced by 16.1 % on average. Li et al. [44] utilize RFID technology to capture real-time location information throughout the on-site assembly of modular integrated construction. The data captured is sent to the cloud for real-time processing and analysis. This helps on-site managers and staff make better decisions, enhance operational efficiency, and improve collaboration and supervision during the assembly of pre-fabricated buildings. Xue et al. [45] examine the existing patterns and trends in RFID-enabled building information modeling systems. They also provide guidelines for choosing suitable solutions in various building project management scenarios and in different construction project management scenarios.

In the field of logistics, Zadgaonkar et al. [120] employ machine-learning algorithms to enhance the precision of BLE beacon localization. The study's findings offer valuable data support for resource discovery, order acceptance, and enhancing the inventory process in warehouse management. Zhao et al. [79] employ ZigBee technology to design an intricate storage environment monitoring system. The aim is to decrease the development cost and energy consumption associated with storage environment monitoring while simultaneously enhancing the efficiency of the monitoring process. Zhao et al. [121] suggest the combined utilization of RFID and UWB technologies in an intelligent warehousing management system. This system leverages UWB technology to determine the location of forklift trucks and utilizes RFID technology to ascertain the status of goods during loading and unloading operations.

4.2.2. Real-time scheduling

Multiple studies have concentrated on implementing IPS in manufacturing to enable real-time resource scheduling. These studies approach the topic from three distinct perspectives: single object, single enterprise, and multiple inter-enterprise. At the single object level, Zhang et al. [122] designed a dynamic optimization of the shopfloor material handling model, where each trolley is an active agent requesting a transportation task compared to traditional material handling methods. Then, the optimal transportation task is allocated to the optimal trolley according to the real-time state. Carrasco et al. [58] introduced a system designed to locate the nearest machine in proximity to the user, which utilizes low-cost BLE beacons and signal strength indicators to achieve machine location acquisition. Zhao et al. [61] devised an architecture for collaborative tracking enabled by IoT edge computing. They also proposed a supervised learning genetic tracking methodology. This architecture and methodology were effectively deployed and implemented in real-life manufacturing industrial parks. As a result, managers were able to gain a comprehensive real-time view of manufacturing resources and accomplish task matching with the closest available resources. At the individual enterprise level, Zhou et al. [50] employ RFID technology to store and transmit the attributes of processing operations. This approach enables online scheduling of multi-variety orders. The proposed methodology is implemented in a smart factory setting and is evaluated through a real case study. The experimental results demonstrate that the smart factory's new architecture enhances the efficiency of multiple schedulers in terms of learning and scheduling. Additionally, it effectively handles unforeseen events, such as emergency orders and machine failures. Chen et al. [123] propose a cost-effective method to reconfigure the production logic. They accomplish this by constructing a discrete event-driven model predictive control, which optimizes real-time WIP to facilitate timely production decision-making. The aim is to prevent any backlog of WIP and ensure smooth production operations. Guo et al. [124] introduce an intelligent decision support system architecture that utilizes RFID technology for production monitoring and scheduling in a distributed manufacturing environment. The proposed architecture has been successfully implemented in a pilot project within an apparel manufacturing environment. It demonstrates good scalability and extensibility, allowing for seamless integration with production decision-making, as well as production and logistics operations within the supply chain. At multiple enterprise levels, Zhang et al. [48] present an architecture for real-time information capturing and integration in the context of the Internet of Manufacturing Things. This architecture enables embedding sensors in various manufacturing resources such as operators, machines, pallets, and materials. The real-time manufacturing information integration service is a crucial architecture component, which facilitates seamless two-way connectivity and inter-operability between different enterprises. Ding et al. [125] introduce a social manufacturing system that utilizes RFID technology to enable real-time monitoring and dispatching across multiple enterprises. This system aims to address sudden disruptions by dynamically scheduling production and transportation tasks among enterprises. Additionally, it enhances the transparency of inter-enterprise production, particularly in the context of large-scale personalization.

Studies also focus on the application of IPS for real-time scheduling in construction and logistics. Altaf et al. [126] applied RFID technology, data mining techniques, and simulation-based optimization to create a production planning and control system for a panelized home prefabrication facility. This system enables managers to capture assembly line production data in nearly real-time and automatically optimize the production schedule, leading to improved efficiency and effectiveness in the facility's operations. Zhao et al. [60] employ iBeacon technology for warehouse management. Their proposed scheme demonstrates the potential to significantly enhance the performance of order picking and inventory processes within warehouse management.

4.2.3. Bottleneck identification

Some studies [83,127,87,105] focus on mechanisms for processing IPS-related data in the manufacturing domain, and some scholars focus on how to implement IPS within factories. Wolf et al. [128] present an innovative framework for IPS in industrial environments. This framework enables continuous monitoring of the current location and parameters (such as speed and direction) of process resources, including operators, equipment, and products. It also collects shop floor data and configures the production system to provide real-time feedback to blue-collar workers. Aydos et al. [129] developed a manufacturing monitoring system that combines RFID, wireless, and plug-and-play technologies. This system collects data on time and WIP to facilitate the identification of process wastage, enable production based on job times, achieve activity balancing, and assess capacity within the manufacturing process. Cao et al. [130] explored the state characteristics of production logistics from the perspective of multi-attributes such as time, place, quantity, sequence, and path, and established a computational model to process RFID data and then discover abnormalities in production logistics. Zhou et al. [131] put forward a comprehensive framework for knowledge-driven digital twin manufacturing cells in the context of intelligent manufacturing. This generic framework facilitates autonomous manufacturing by incorporating intelligent sensing, simulation, understanding, prediction, optimization, and control strategies. It can be applied to various aspects of intelligent manufacturing, including intelligent process planning, intelligent production scheduling, and production process partitioning.

Several studies in construction and logistics apply IPS to bottleneck identification. Li et al. [132] developed an RFID-enabled building information modeling platform. This platform integrates multiple stakeholders, information flows, offshore prefabrication processes, and advanced construction technologies. Its purpose is to streamline operations across the three echelons of prefabrication, logistics, and on-site assembly of the building. The platform utilizes real-time data capture to establish a closed-loop visibility and traceability model, enabling different end users to monitor construction status and progress in real-time. This real-time monitoring capability helps mitigate critical schedule risks. Zhao et al. [133] introduce a proactive tracking system architecture that utilizes iBeacon technology and distributed gateway concepts. This architecture incorporates location-based service triggers and seamlessly integrates location information with warehouse workflows. It aims to reduce time wastage in the order picking and inventory processes. The system also enables the dynamic location information of products to be known and updated, enhancing overall efficiency in warehouse operations. Kong et al. [134] presented a cloud platform that supports a multi-layer physical internet concept. This platform enables virtualization and real-time control of logistics assets, facilitating reconfigurable task coordination and execution. It also allows for simultaneous on-time process synchronization. By leveraging this cloud platform, logistics operations can be optimized for efficiency and responsiveness.

4.3. Safety management

4.3.1. Staff states monitoring

Ongoing research efforts have been made to leverage this technology for staff state monitoring on construction sites. Gómez-de-Gabriel et al. [98] introduced an innovative approach to actively regulate the power of a tool based on the worker's distance from it. This solution serves the dual purpose of detecting hazardous situations resulting from improper use of personal protective equipment or incorrect tool proximity and promptly and effectively intervening to mitigate safety risks. Consequently, it effectively addresses safety concerns in construction projects involving the utilization of power tools. Kanan et al. [135] proposed an innovative design for an autonomous system. This system is designed to actively monitor, identify whereabouts, and issue warnings to construction workers operating in high-risk zones. Its primary objective is to ensure the safety of construction workers and prevent accidents at construction sites. Chen et al. [136] recognized the significance of position and posture as crucial quantitative indicators. They introduced the concept of fusing position and posture to evaluate the behavioral safety risks of construction workers. The fusion principle combines posture, position, and the fusion of posture and position to determine the level of risk for individuals involved. Zhang et al. [55] employed an RFID system to efficiently detect the entry and exit actions of workers carrying tags upon entering the construction site. Additionally, they utilized virtual zones of different sizes and shapes, created in a flexible manner, to identify intruders and issue timely warnings. This approach effectively contributes to accident prevention at construction sites. Maalek et al. [71] conducted a study examining the feasibility of UWB technology for resource localization in construction sites. They further integrated this technology with managing hazardous areas on construction sites, aiming to enhance existing safety monitoring practices. Their research highlights the potential of UWB as a valuable tool for improving safety measures in construction environments.

The logistics industry has been at the forefront of exploring the application of IPS for staff states monitoring. Halawa et al. [70] employed IPS to track and locate forklifts and other mobile entities within a warehouse setting. They established a connection between this information and the warehouse and forklift fleet management systems. Through this integration, they could analyze routing strategies, operating speeds, congestion identification, intersection driver patterns, and fault analysis. Their approach aimed to enhance both the safety and operational efficiency of the warehouse environment. Zhao et al. [137] presented a safety management tracking solution that leverages the IoT and digital twins. Their approach involves the establishment of an indoor safety tracking mechanism, which enables the detection of stationary behaviors. Additionally, they employed self-learning genetic localization techniques to identify personnel anomalies and obtain precise real-time location information. By combining IoT and digital twin technologies, their solution aims to enhance safety management practices by enabling accurate tracking and anomaly detection in indoor environments. Zhan et al. [138] introduce an intelligent system framework that utilizes industrial IoT and DT technologies. Their framework aims to enable real-time monitoring of occupational safety in warehouse environments. By leveraging industrial IoT and DT, the system ensures that the physical space and corresponding information are synchronized, allowing for traceability and visibility of operations. This integrated approach enhances safety monitoring practices and promotes efficient management in warehouse settings. Wu et al. [139] presented a cyber-physical platform framework that leverages the internet of everything and DT technologies. This framework aims to enable seamless information integration and deliver intelligent services to various stakeholders in the cold chain logistics domain. The proposed platform facilitates real-time supervision of personnel safety in cold storage facilities, enables paperless transportation operations, allows for remote monitoring of temperature and humidity, detects anomalies, and provides alerts. Additionally, it supports customer interactions, enhancing overall operational efficiency and safety in the cold chain logistics industry.

4.3.2. Collision prevention

Some studies have introduced IPS to prevent collisions. In the field of manufacturing, Neal et al. [54] examine the potential of recyclable transportation objects as intelligent containers within the context of cyber-physical manufacturing services. They explore how these containers can interact with components, machines, and other elements of the manufacturing system. Additionally, they focus on the identification of intelligent components and the monitoring of the logistic handling process. This includes the detection of collisions, lifting actions, and turning movements. The research sheds light on the role of intelligent containers in enhancing efficiency and safety in manufacturing operations.

In addition, applying collision prevention of IPS in construction is another domain. Ventura et al. [140] devised an affordable proximity detection system utilizing UWB technology. This system can operate with or without fixed anchors and gathers real-time data directly from the construction site. Its primary function is to alert workers to potential collision hazards, ensuring their safety on the job.

4.3.3. Hazard detection

Emerging research has explored the application of IPS for hazard detection. In the field of manufacturing, Sellak et al. [141] introduced a system that combines UWB positioning technology with vibrating undershirts to offer tactile proximity warnings to workers. By continuously monitoring the workers' location in relation to hazardous areas, the system effectively alerts them to potential dangers. This innovative approach has the potential to enhance both the safety and productivity of the industrial workforce by reducing workplace accidents, injuries, and fatalities.

In addition to industrial applications, the integration of IPS for hazard detection has also gained traction within the construction industry. Arslan et al. [64] proposed WoTAS, which enables safety managers to remotely monitor and control construction activities in a dynamic environment. By tracking and analyzing the trajectory of workers, WoTAS facilitates a better understanding of their activities. Consequently, it enhances safety management in day-to-day construction operations, enabling proactive measures to be taken to ensure worker safety. Huang et al. [63] devised a method using BLE to detect proximity areas and deliver proximity safety alerts to workers on construction sites. This method employs BLE technology to accurately identify proximity and promptly generate vibrotactile alerts. These alerts are designed to be easily perceived by workers, ensuring timely warnings and promoting safety awareness in construction environments.

4.4. Summary of previous work

Although this topic has been extensively researched over the past 10 years, several aspects have received little or no attention to date. Cost and latency are important factors affecting the choice of indoor positioning technology for industrial applications, but few studies have considered the deployment cost, maintenance cost, and latency of IPS for large-scale, long-duration applications in the industry. In addition, indoor positioning system robustness is also a consideration for industrial applications of IPS, yet only a few studies [125,77,97] have considered system robustness. In industrial environments, indoor localization systems are bound to receive a variety of noises. Although some studies [43,142] consider noises in production environments, the diversity and randomness of noises in real production situations need to be further explored. The above limitations can make it difficult for the industry to adopt IPS directly.

The accuracy of IPS in different studies also varies greatly, which is closely related to the choice of technology and algorithm, the testing environment, and the deployment environment. However, some studies do not disclose detailed information about the setups used to test the positioning systems, and there is no common test standard that can be used for reference to specify the testing requirements in detail to make the accuracy of the tested systems replicable and migratable. For example, Ma et al. [74] designed the enhanced MaLoc module using indoor positioning with magnetic fields and Wi-Fi signals, which provides 2D positioning services with an accuracy of 1–2.8 m without mentioning any obstacles or any other factors that may affect the accuracy of the system. Carrasco et al. [58] used a BLE beacon for each machine, and with the help of the localization system, the guessing rate of the machine was about 89 % correct but they did not analyze the factors affecting the rate or how to improve the rate of guessing and its correctness.

5. Directions for future work

Summarizing the research priorities and research content based on the analysis of currently available articles is particularly beneficial in identifying important aspects that have not yet been adequately investigated, as well as the main areas for future research. This section summarizes these aspects in terms of recent developments in IPS, the use of spatial-temporal data, and the conjunction of indoor positioning and machine learning.

5.1. Potential value of spatial-temporal data

In the era of Industry 4.0, making full use of spatial and temporal data to drive industrial transformation and upgrading has become an imperative trend. As the indoor positioning system of Industry 4.0 spatial and temporal infrastructure, it provides key positioning information for various industrial scenarios, bringing many application values.

First, IPS can track the location of production equipment, materials, and personnel in real-time, providing data support for production process management and logistics optimization. For example, real-time monitoring of the location and use of key equipment can help companies identify bottlenecks in the production line in a timely manner and take measures to optimize. At the same time, through the real-time positioning of raw materials and finished products, enterprises can optimize warehousing and transportation paths, improve inventory turnover efficiency, and significantly reduce logistics costs. In addition, safety management based on personnel positioning is also a major application value of IPS. Through real-time tracking of the location of the operating personnel, enterprises can find abnormalities in a timely manner and take appropriate emergency measures to avoid the occurrence of safety accidents effectively. For example, regional control in hazardous areas should be implemented to limit the entry of unauthorized personnel and minimize potential safety hazards. At the same time, companies can also use positioning data to analyze the employee's work behavior, optimize the workflow, and further enhance the safety of the production environment. Overall, IPS for production process management and safety production provides a new solution through real-time mastery of equipment, materials, and personnel location information. Companies can gain insight into the production line operating conditions and optimize logistics and safety management, thus significantly improving production efficiency and safety levels.

Secondly, spatial-temporal data can also be used to enhance the intelligent management and maintenance of equipment. By monitoring the operating status and utilization of key equipment, enterprises can discover the first signs of equipment failure and take timely maintenance or adjustment measures. At the same time, based on the analysis of the frequency of use of equipment and environmental conditions, enterprises can optimize the maintenance plan and rational arrangement of maintenance cycles to extend the service life of equipment. For example, companies can increase the maintenance frequency for high-frequency use or harsh environment equipment. For less use of the equipment, companies can extend the maintenance cycle. This intelligent operation and maintenance mode based on spatial-temporal data not only can minimize the equipment failure rate and reduce production interruption but also effectively improve the overall reliability and utilization of equipment, thus creating more economic value for the enterprise. Overall, the application of spatial-temporal data can not only optimize production and logistics management but also realize the intelligent maintenance of equipment for the digital transformation of enterprises to inject new momentum.

In addition, the IPS, which collect personnel and material flow data, can also be used to optimize the layout of the factory and the design of the line. Combined with the process flow and production demand, enterprises can analyze the actual movement of materials and personnel trajectory to identify the production line of the blockage and inefficient areas. Based on this, enterprises can adjust the layout of workstations and shorten the distance of material and personnel movement, thereby reducing production costs and time loss. At the same time, these spatial and temporal data can also be used to provide data support for new or modified production lines. Enterprises can utilize simulation technology to assess the efficiency of personnel and material flow according to different production line planning schemes. In addition, enterprises can also compare the production indicators under various programs to provide a scientific basis for the final layout decisions and ensure the rationality and reliability of the factory layout. Overall, the spatial-temporal data collected by IPS can not only be applied to production process management and equipment maintenance but also provide essential support for the optimization of the factory layout and the design of the moving line, maximizing the efficiency and flexibility of the entire production system.

Further, based on the real-time positioning of human-machine collaboration, companies will significantly enhance the level of factory intelligence. For example, through the personnel location-aware equipment remote control, the operator does not need to arrive at the location of the equipment personally, and the equipment can be operated and adjusted, significantly improving work efficiency. At the same time, according to the environmental conditions of the area where different operators are located, the system can automatically adjust the temperature and humidity, lighting, and other parameters to create a more comfortable working environment for the operators and further improve work efficiency and safety. In addition, with the use of positioning data, the enterprise can optimize the autonomous decision-making ability of the equipment so that it can be operated based on the location and status of the operator. In general, based on spatial-temporal data, human-machine collaboration will become one of the core technologies for the construction of future smart factories. The realization of personnel, equipment, environment, comprehensive perception, and intelligent interconnection not only can improve production efficiency and reduce operating costs but also inject new momentum for intelligent manufacturing of the Industry 4.0 era.

Finally, the spatial and temporal data provided by the indoor positioning system can also be used to build a digital twin model, realizing a high degree of integration between the virtual factory and the physical factory. By importing the real-time operation data of equipment, process, personnel, and other elements of the actual factory into the virtual model, enterprises can conduct simulation and analysis in the digital twin system to optimize production planning, logistics and distribution, equipment maintenance, and other aspects, and feedback the optimization scheme to the physical world in a timely manner to improve the overall operational efficiency. At the same time, combined with augmented reality technology, enterprises can also provide operators with digital twin system visualization guidelines to help them more intuitively grasp the equipment operation process, production process points, etc., to improve the quality of operations and safety. Overall, the digital twin model based on spatial-temporal data not only realizes the deep integration of the virtual and physical world but also lays the foundation for the development of Industry 5.0. Through continuous optimization of the virtual model, enterprises can continue to improve the intelligent level of production and operation and ultimately realize the digital transformation of the entire value chain of the factory.

In short, IPS, as the infrastructure of spatial-temporal data, are helping the industry to achieve intelligent transformation in the era of Industry 4.0. By improving production efficiency, enhancing equipment management, optimizing factory layout, promoting human-computer interaction, as well as the realization of digital twins and other innovative applications, IPS are becoming an essential driving force for the transformation of Industry 4.0 to Industry 5.0, helping the industry to achieve the entire value chain of intelligence and digitalization.

5.2. Enhancement of suitability

Eliminating multipath effects and noise interference is a critical technical bottleneck that needs to be addressed when applying IPS in industrial environments. The multipath effect arises due to the reflection, refraction, and diffraction of signals on obstacles such as walls, metals, and human bodies, which seriously affects the propagation behavior of signals. Future research directions can be approached from some perspectives.

First, multipath compensation algorithms based on environmental awareness can be explored. The key of this method is to utilize various kinds of sensing devices that already exist inside the factory, such as cameras and radars, to obtain real-time environmental information. Through these environmental data, companies can establish the electromagnetic propagation model inside the factory and predict the multipath propagation characteristics of the signal under different environmental conditions. For example, based on the distribution of walls, equipment, personnel, etc., the model can predict the paths in which signals will be reflected and diffracted, resulting in multipath effects. With this prediction information, companies can incorporate it into the positioning algorithm to compensate and correct the measurement data, and ultimately improve the positioning accuracy of the positioning system. This environment-aware multipath compensation algorithm can fully utilize the factory's existing infrastructure without additional deployment costs, which is a promising technology direction for solving multipath interference.

Secondly, new positioning technologies for industrial environments are also worthy of attention. Compared with general consumer applications, industrial environments have their own unique characteristics, requiring targeted technical solutions. A feasible idea is to use the wireless communication module that comes with the industrial equipment, such as industrial control gateway, industrial robots, etc., as a positioning node to build a positioning network specifically for the industrial scene. This approach can fully utilize the existing industrial equipment resources without additional deployment costs. At the same time, researchers can explore the use of UWB, millimeter waves, and other new wireless technologies for the complex electromagnetic environment in the industrial environment. These techniques are highly resistant to multipath and are more suitable for use in factories and other complex indoor environments. In addition to innovation at the hardware level, researchers also need to develop intelligent cooperative positioning algorithms for Industry 4.0. Combined with the intelligent control system of industrial equipment, the positioning algorithms can realize the collaborative sensing and linkage between the equipment to improve positioning performance and reliability further. In general, these new positioning technologies for industrial environments will help to solve the thorny problems of multipath interference and provide strong support for factory automation and intelligent manufacturing.

Finally, the use of machine learning techniques to optimize positioning performance is also a research area with great potential. Compared with traditional localization algorithms, machine learning methods can be better adapted to the complex and changing factory environment. One feasible idea is the adaptive localization algorithm based on environment modeling. Companies can utilize machine learning techniques to build a detailed environment model from all kinds of factory environment data, such as floor plans, equipment distribution, personnel activities, etc. With such an environment model, the localization algorithm can automatically adjust the parameters and strategies according to the changes in the real-time environment and improve adaptability to multipath and interference. In addition, the use of deep learning to mine hidden patterns and knowledge from massive positioning data is also a direction worthy of attention. Deep learning algorithms can automatically extract the complex features contained in the positioning data and then build accurate positioning models. This data-driven localization method has good mobility and generalization ability in complex industrial environments, which helps to further improve the performance and reliability of the localization system. In conclusion, the application of machine learning techniques to the optimization of IPS is a research field full of imagination and development potential.

In conclusion, solving the problems of multipath effect and noise interference is the key to realize the high reliability and high accuracy of IPS in the industrial environment. The above research directions are expected to provide adequate technical support for this.

5.3. Privacy and security

When applying IPS in industrial environments, privacy and security factors need to be emphasized. Employee location information is private data. If this data is not effectively protected, it can lead to privacy leakage and affect the trust of employees. At the same time, the factory's positioning system is connected to various industrial networks, which makes the positioning system susceptible to cyber-attacks and malicious tampering, threatening the security and reliability of the positioning system. In addition, as privacy regulations become increasingly stringent, factories must ensure privacy compliance with their positioning systems or face regulatory risks. In summary, companies can only facilitate the successful implementation of positioning-based applications in Industry 4.0 by adequately addressing privacy and security issues. In response to this demand, researchers can conduct research and exploration from various aspects.

First, effective privacy protection techniques are needed to minimize the risk of privacy leakage while preserving the positioning function. Differential privacy techniques can be used to enhance the privacy of employees' location data and reduce the risk of privacy leakage by introducing random noise to blur the real location information. Federated learning technology can avoid centralized storage of employee location data and perform distributed machine learning model training without sharing the original data, which reduces the potential risk of data leakage from the root. We can also study the data aggregation method for privacy protection and utilize homomorphic encryption, secure multi-party computation, and other technologies to realize location data aggregation and statistical analysis without disclosing personal privacy. At the same time, the system design should fully consider the privacy feelings of employees and provide privacy preferences and other humanized functions to enhance the trust of employees. Finally, ensuring that the design of the positioning system complies with the latest privacy protection regulations, such as the general data protection regulation and the personal information protection act, is also an important direction that deserves attention.

Secondly, the cryptographic security authentication mechanism is an important direction worthy of in-depth study. Enterprises can consider using public key infrastructure technology to establish a trusted identity authentication system, ensuring the identity legitimacy of each subject in the system (such as employees, equipment, etc.) through digital certificates, digital signatures, and other means. By studying the identity authentication scheme based on zero-knowledge proof, safe and reliable identity authentication can be realized without disclosing personal privacy information. In addition, combined with attribute-based encryption, selective disclosure, and other cryptographic techniques, fine-grained access control to system resources is realized. According to the roles and permissions of different subjects, the access and operation of sensitive information, such as positioning data and system configuration, can be flexibly controlled to prevent illegal leakage and tampering of information. At the same time, advanced symmetric encryption, public key encryption and other algorithms are used to encrypt the end-to-end transmission and storage of positioning data to ensure the confidentiality and integrity of the data in the process of network transmission and internal system flow. Moreover, the distributed ledger and consensus mechanism of blockchain are utilized to establish a credible data-sharing model, and the rules of data access and use are stipulated through smart contracts to realize safe and reliable data exchange across subjects. Finally, the cryptography-based system log and auditing procedures are studied to ensure the traceability and non-repudiation of the system operation activities and provide a reliable basis for after-action analysis and traceability.

The network security protection technology in IPS is also a vital direction worthy of in-depth research. First, the programmable characteristics of network security protection based on software-defined networks can be combined with machine learning technology to achieve real-time monitoring and intelligent analysis of indoor positioning network traffic. With the help of this process, various network attacks, such as illegal access and data theft, can be discovered and prevented in time. In addition, the sensing and computing capabilities of indoor positioning sensing devices can be fully utilized to establish a distributed security monitoring system to realize IoT network security monitoring. Studying the decentralized security monitoring mechanism based on blockchain is also a worthwhile research topic, as it can effectively improve the trustworthiness and risk resistance of the monitoring system. Again, the security isolation protection based on an indoor positioning gateway is also a worthy research direction. By deploying secure and trustworthy gateway devices in key areas, external network attacks can be effectively blocked to protect data security inside the IPS. Besides, security reinforcement based on indoor positioning communication protocols can be considered. Digital signatures and message authentication codes are added to the positioning data communication to ensure the integrity and authenticity of the data. Alternatively, an attribute-based access control mechanism can be introduced to restrict illegal access to critical functions. Finally, based on security reinforcement, combined research on intelligent vulnerability scanning and patching technology based on machine learning can effectively improve the self-healing ability of the system. The research of these network security protection technologies will provide an effective guarantee for the safe and reliable operation of IPS.

In addition to network security protection, privacy compliance is also a key concern when positioning systems are applied in industrial scenarios. First, data anonymization techniques, such as data desensitization, forgery, aggregation, and other means, can be used to protect the privacy of the collected positioning data to ensure that the individual's private information will not be leaked while maintaining the validity and usability of the data. Secondly, differentiated positioning services can be designed to allow users to independently choose the level of privacy to improve the user's perception of privacy and trust. In addition, a clear privacy policy should be formulated to regulate data collection, storage, use, and sharing. A third-party monitoring mechanism and a credible privacy data management platform should be established by utilizing blockchain and other distributed ledger technologies. At the same time, privacy enhancement technologies such as differential privacy, homomorphic encryption and secure multi-party computation are integrated into the key aspects of the positioning system to further improve the privacy protection capability of the system. Finally, users are empowered to make decisions on their own private data, and a flexible data-sharing authorization mechanism is established to allow users to independently control the scope of use and authority of their personal information. In conclusion, privacy compliance is an important design goal in the application of industrial positioning systems. In-depth research and innovation from multiple dimensions, such as technology, management, and service, are of great significance in enhancing user trust and promoting the healthy development of the industry.

By adopting these adequate privacy protection and security measures, the industrial positioning system can not only meet the actual application requirements but also maximize the protection of employees' personal privacy and provide reliable technical support for the intelligent transformation of industries.

5.4. Energy efficiency

Energy efficiency is a very important consideration when applying IPS in industrial environments. First, IPS usually involves many hardware devices and complex software systems, with a large scale of overall energy consumption. If the energy consumption of an IPS is not appropriately managed, this will result in a colossal waste of energy. Second, IPSs need to run for a long time to meet production demands, so the energy consumption problem will persist and cannot be ignored. In addition, the improvement of industrial energy efficiency is crucial to promote the current green transformation in the industrial sector, and the IPS, as an important part of the industrial IoT, has a direct impact on the energy consumption of the whole factory. Therefore, when deploying the IPS indoor positioning system, full attention should be paid to the energy efficiency issue, and effective optimization measures should be taken. Optimization measures can not only reduce the operation cost of the system itself but also contribute to the energy saving and emission reduction of the whole enterprise, industry, country, and even the earth. The following section describes the relevant research directions.

Firstly, low-power positioning solutions based on emerging wireless technologies such as BLE and UWB can be explored at the wireless communication technology level. These technologies have lower power consumption characteristics compared to traditional Wi-Fi, RFID, etc. The operating current of BLE chips can reach the microamp level, and UWB has higher time resolution and better multipath suppression, which can minimize the energy consumption of positioning devices. At the same time, based on these emerging wireless technologies, further optimization of positioning algorithms and communication protocols is needed to improve their positioning accuracy and energy efficiency. For example, efficient positioning algorithms based on RSSI, TDoA, AoA, and other technologies can be studied and combined with machine learning and compressed sensing to improve the computational efficiency of the algorithms. At the communication protocol level, it is necessary to optimize the data transmission mechanism for different application scenarios and reduce unnecessary communication overhead, thus further improving the system's energy efficiency.

Secondly, the working mode and power output of the positioning equipment can be dynamically adjusted according to the actual process flow, operating time, and other demand characteristics. Different production environments and work tasks on the performance requirements of the positioning system are different, so companies need to flexibly adjust the positioning equipment according to the specific circumstances of the working state. For example, in idle or non-critical time, companies can turn the positioning equipment into low-power mode, turn off unnecessary sensors and communication modules, and reduce power output, thereby reducing unnecessary energy consumption. In critical production processes, equipment can be switched to high-performance mode to ensure positioning accuracy and real-time. By dynamically adjusting the working mode, the overall energy consumption can be minimized while meeting the business requirements. In addition, researchers can study the hybrid power supply scheme based on energy harvesting technology, utilizing solar energy, vibration energy, thermal energy, and other environmental energy sources to supply power for positioning equipment. This approach can reduce the dependence on the power grid and improve the overall energy utilization efficiency. Moreover, the use of efficient energy management and storage technologies, such as supercapacitors, secondary batteries, etc., can ensure that the equipment can continue to work stably even when the environmental energy is insufficient.

In addition, the use of distributed positioning architecture is also a feasible direction. The traditional centralized positioning system concentrates all the computation and communication tasks on the central server, which increases the energy consumption overhead of the system to a certain extent. In contrast, a distributed localization architecture can reasonably share the localization task with each node. With the technology of edge computing and inter-device collaboration, positioning algorithms and communication processing can be completed on edge devices close to the data source, which reduces the transmission of data in the network and the computational and communication load of the central server. For example, intelligent sensor nodes can be used to perform preliminary positioning calculations and only upload the final positioning results to the central server. Alternatively, a distributed positioning network can be formed through mutual positioning and collaboration among devices to achieve load balancing and energy consumption optimization. At the same time, this distributed architecture can also improve the robustness and scalability of the system, which is more conducive to large-scale deployment. By adopting a distributed positioning architecture, companies cannot only reduce the energy consumption overhead of the whole system but also improve positioning performance and reliability.

At the same time, it is also essential to establish a mechanism for monitoring and analyzing the energy consumption of the whole life cycle of the positioning system. In the industrial IoT environment, the positioning system involves many hardware devices and software systems, and it is necessary to control the energy consumption of the whole system comprehensively. Through real-time monitoring of the power consumption of each device, abnormal power behavior can be found in a timely manner, such as excessive power consumption of specific devices or abnormal work mode. Based on these monitoring data combined with big data analysis technology, the key factors affecting system energy consumption can be explored in-depth, and targeted optimization strategies can be proposed. For example, the power of the equipment can be dynamically adjusted according to different operating hours, or the positioning algorithm and communication protocol can be optimized to further reduce the overall energy consumption of the system. At the same time, machine learning and other methods can be used to build energy consumption prediction models to provide decision support for system operation and maintenance and realize adaptive energy management.

Finally, the deep integration of the positioning system and the energy management system of the factory is also a direction worthy of attention. Industrial production process, equipment location information, and energy consumption data are closely related. Through the synergistic analysis of these two types of data, companies can tap into more optimization potential. For example, by combining the real-time location information of the equipment, companies can accurately identify the energy hotspots on the production line and find out which areas or equipment have higher energy consumption. Based on such a nuanced picture of energy consumption, the factory's energy management system can automatically schedule the energy supply and put more resources into key equipment and processes, thus optimizing the overall energy efficiency. At the same time, the positioning system can also provide a more auxiliary decision-making basis for energy management. For example, according to the trajectory of the equipment, companies can predict future changes in energy demand, so energy can be deployed in advance. Enterprises also coordinate the peak energy consumption of different processes in conjunction with the process flow, thereby realizing peak and valley load balancing. This location-based energy management can realize the deep integration of energy supply and production processes, significantly improving the overall energy utilization level of the factory.

In conclusion, energy saving is also an important design goal in the application of IPS. Enterprises can carry out in-depth research and practice in technological innovation, intelligent management, distributed architecture, etc., which is of great significance for reducing their operating costs and realizing green production.

6. Conclusion

This paper provides a comprehensive review of the use of different IPS in industrial applications within the context of Industry 4.0 from 2014 to 2023, based on an analysis of 175 relevant journal articles. The leading indoor positioning technologies covered include RFID, UWB, BLE, Wi-Fi, and ZigBee, and the researchers have explored their applications in various industry-related use cases such as position detection, collision avoidance, process control, and resource allocation. Indoor positioning can track all production resources, including hand tools, personnel, materials, and work-in-progress. Most of the considered applications occur in the production, logistics, quality control, and assembly phases, with fewer in the maintenance and disassembly phases. This article also discusses and summarizes the advantages, limitations, costs, and features of different IPSs. In addition, the article innovatively categorizes the application of IPS in Industry 4.0 into three main categories and nine subcategories of scenarios. This is the first systematic summary of the role of IPS in enabling industrial scenarios in the Industry 4.0 context. While the method used to select the sample data introduces some bias, as it does not include unpublished conference papers, the study provides a valuable synthesis of the available information from both academia and industry.

Future research can further explore the wide range of applications of IPS in Industry 4.0 to fully realize its potential value. This includes studying hybrid positioning technologies that combine the strengths of different systems, such as RFID, UWB, BLE, Wi-Fi, and ZigBee, to achieve more accurate and reliable indoor positioning. Integrating these localization technologies with IMU, machine vision, simultaneous localization and mapping (SLAM), and other sensing modalities could further improve positioning performance. Machine vision and SLAM technologies can enhance the accuracy and robustness of localization. By fusing vision information and environment modeling, the positioning system compensates for the limitations of a single positioning technology and provides a more comprehensive positioning solution. Additionally, researchers should investigate indoor/outdoor fusion positioning systems to enable seamless switching and continuous positioning as users transition between indoor and outdoor environments. This could involve integrating outdoor positioning technologies like satellite-based and mobile network-based solutions with the indoor positioning system to meet the complex localization requirements of industrial scenarios. Beyond just improving the positioning capabilities, researchers should also explore how indoor positioning can be integrated with spatial and temporal information about the production processes. IPS can generate valuable insights to optimize critical functions such as production, logistics, and quality control by analyzing the relationship between location, time, and various operational metrics. Furthermore, the applications of IPS should be expanded into emerging fields such as low-carbon management, dynamic optimization, and resource protection within the Industry 4.0 context. This would help unlock the full potential of IPS in supporting the complex and evolving needs of modern industrial environments. Overall, future research should focus on innovating hybrid and fusion positioning technologies while also broadening the breadth and depth of IPS applications to stay ahead of the changing requirements in the Industry 4.0 era.

CRediT authorship contribution statement

Peisen Li: Writing – original draft, Investigation, Data curation. **Wei Wu:** Writing – review & editing, Methodology. **Zhiheng Zhao:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **George Q. Huang:** Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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No data was used for the research described in the article.

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