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Systematic Review

Smartphone-Based Indoor Localization Systems: A Systematic Literature Review

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Abstract: These recent years have witnessed the importance of indoor localization and tracking as people are spending more time indoors, which facilitates determining the location of an object. Indoor localization enables accurate and reliable location-based services and navigation within buildings, where GPS signals are often weak or unavailable. With the rapid progress of smartphones and their growing usage, smartphone-based positioning systems are applied in multiple applications. The smartphone is embedded with an inertial measurement unit (IMU) that consists of various sensors to determine the walking pattern of the user and form a pedestrian dead reckoning (PDR) algorithm for indoor navigation. As such, this study reviewed the literature on indoor localization based on smartphones. Articles published from 2015 to 2022 were retrieved from four databases: Science Direct, Web of Science (WOS), IEEE Xplore, and Scopus. In total, 109 articles were reviewed from the 4186 identified based on inclusion and exclusion criteria. This study unveiled the technology and methods utilized to develop indoor localization systems. Analyses on sample size, walking patterns, phone poses, and sensor types reported in previous studies are disclosed in this study. Next, academic challenges, motivations, and recommendations for future research endeavors are discussed. Essentially, this systematic literature review (SLR) highlights the present research overview. The gaps identified from the SLR may assist future researchers in planning their research work to bridge those gaps.

Keywords: indoor localization; smartphone; pedestrian dead reckoning; walking pattern; IMU sensors

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1. Introduction

Indoor localization is an essential function required for location-aware applications in pervasive computing environments [1]. Location-based services (LBS) depend on the accurate and continued localization of users. The LBS is required in several fields, such as emergency security, crowd monitoring, intelligent warehousing, precision marketing, mobile health, augmented reality, and other significant fields [2]. These applications determine the location of mobile objects or people. Most applications currently depend on the global positioning system (GPS) [3]. Apart from its sensitivity to occlusions (e.g., ceilings and walls), GPS is ineffective and unsuitable for indoor localization [4–7]. Meanwhile, the global navigation satellite system (GNSS) signal suffers from degradation due to signal reflection [8], signal attenuation [9,10], weak reception of satellite signals [11–13], and signal fluctuation that leads to major localization error [4]. When applied in an indoor or indoor-like environment, GNSS poses significant obstacles. Although GPS has been the most extensively used outdoor localization tool, no standard method exists for indoor localization [1]. Indoor localization and tracking are, therefore, important topics for discussion in the academic domain [14–16].

Researchers have developed different technologies to provide accurate indoor localization and tracking, such as approaches based on Wi-Fi [17], Bluetooth [18], Radio-frequency Identification (RFID) [19,20], acoustic [21,22], and inertial sensors [23]. In order to achieve localization, Wi-Fi and Bluetooth are required for the installation of additional infrastructure. As for RFID, it requires active or passive tags with the localization environment or the user, along with a scanner [19]. Acoustic waves enable target localization with centimeter-level accuracy, but the localization system is easily impaired when reflected or obstructed by walls or other objects [24]. Next, received signal strength (RSS) or received signal strength indicator (RSSI) is a measurement of the strength of a received radio signal. In theory, the RSS value decreases as the distance between transmitter and receiver increases [25].

Pedestrian dead reckoning (PDR) is a localization approach that calculates the location of a pedestrian using IMU data. Some studies on PDR have assessed step detection, step length estimation, heading estimation, and position estimation using step length and heading information [19,26]. It is one of the most common methods for localization estimation used in smart devices [18]. Notably, each technique has some setbacks in terms of accuracy, cost, coverage, complexity, and applicability. With the progression of smartphone computing capability and distribution, the use of position-detecting methods based on smartphone sensors has become common [25,27].

Micro-electro-mechanical systems (MEMS)-based IMUs are embedded in most smartphones and tablet devices due to their attractive properties, such as low cost, small size, and low power consumption [28]. Since the smartphone-based position estimation system involves many sensors, it comes with high processing power, connectivity, and display to share/retrieve useful information [29]. It is equipped with embedded IMUs, such as accelerometers, gyroscopes, magnetometers, and barometers [2]. Another noted advantage is that it uses only one system instead of integrating Wi-Fi, radio frequency, or GPS signals. Integration with other systems escalates cost and complexity [27], but placing sensors on the body or clothing limits their applicability [30].

The smartphone is equipped with multiple sensors that enable the detection of walking patterns and behavior [23]. The walking pattern represents the global motion of pedestrians, including walking, running, moving upstairs or downstairs, as well as going up or down on elevators or escalators. Data gathered by the inertial sensors contained in the smartphone can identify the activities performed by the person holding the device [31]. The data are used to enhance localization, which can improve location accuracy at a low cost [30]. Walking patterns enhance one's step length estimation, thus increasing localization accuracy. However, one challenge of activity recognition is feature extraction [32,33].

Different approaches have been used to classify pedestrian activity states and phone poses in a wide range of contexts and applications. Neural networks (NNs) can perform many tasks, such as classification of patterns, approximation of function, prediction, categorization, time series prediction, and optimization [34,35]. Machine learning (ML) necessitates the manual computation of features for the classifier, which is potentially limited by a user's subject knowledge [36]. Deep learning acts in the same way, but it takes a longer time to train due to the requirement of a significant amount of data [37–39]. Deep learning methods give good results and dismiss expansive data pre-processing [30]. This is because; deep learning approaches combine feature extraction and classification with nearest neighbor (NN) to identify features automatically instead of using a manual method [32].

1.1. Existing Survey Articles

Although [40] discusses the challenges associated with these methods. It focuses solely on smartphone sensors. However, this research analyzes how smartphone sensors use data from one or more sensors to determine a user's indoor location and provides a comprehensive assessment of these methods. Meanwhile, the detailed survey in [41] aimed at a review of the localization and positioning of human users and their devices, with a particular emphasis on methodologies (Angle of Arrival (AoA), Time of Flight (ToF), Return Time of Flight (RTOF), and RSS) based on technologies (WiFi, RFID, Ultra-Wideband (UWB), Bluetooth). This study has provided a complete overview of the several important elements that must be addressed while designing and assessing indoor localization systems. In addition to highlighting IoT issues created by indoor localization. Next, a comprehensive survey was conducted by [42]. It covers recent achievements in wireless indoor localization from the device perspective, with a focus on exploiting smartphones to combine wireless and sensor abilities and the extraction of specific wireless traits to trigger unique human-centric, device-free localization. Huthaifa et al. [43] present a review article on wireless and navigation system technology, as well as detecting approaches. Upon assessing the crowd-powered methods, ref. [44] offers indoor localization solutions based on crowd sensing or crowdsourcing. Crowdsensing works on the same principles as crowdsourcing, except that the data is collected by devices or sensors rather than by humans. Another survey article from [45] focused on the theoretical techniques and applications for indoor and outdoor that consider location information has been investigated. However, in these survey papers, they did not apply a standard methodology, such as the SLR methodology.

Walter et al. [46] conducted a study on indoor navigation and positioning systems. However, the study focused on blind people. Further analysis includes systems for indoor positioning without calibration [47], WLAN-based cellular localization systems and solutions [48], and indoor localization methods that focus on visible light [49]. However, none of them were concerned with pedestrian activity in indoor localization. They briefly mentioned computer vision-based approaches for indoor localization, including pros and cons [50], navigation, and positioning systems based on computer vision [51]. However, they are focusing solely on the computer vision domain.

Sylvia et al. [52] focus on privacy in navigation systems in SLR. Another SLR [53] overview of cooperative indoor positioning systems. However, they selected the articles from only two datasets, and many articles are missing from other datasets. Luan et al. [54] present a comprehensive view of what indoor positioning systems are capable of based on heuristic information and methodologies as well as accomplishments and limitations in SLR. However, the study focused on the heuristic. Another SLR article that is related to our survey discussed vision-based indoor navigation by identifying various key factors and also focused on robot navigation, AR as visualization, and wearable devices based on systems [55]. However, the scope of the research in computer vision. Turning to the study presented here, it presents a systematic analysis of the accomplishments reported in previous studies for smartphone-based indoor localization. This study reveals the technologies and methods applied to develop indoor localization systems, along with sample size, walking patterns, phone poses, and sensor types. After that, this study outlines the academic challenges, motivations, and recommendations for future research work.

1.2. Motivation and Contributions

In general, the study of indoor localization aims to provide accurate and reliable location information in indoor environments. This is important for a range of applications, including navigation and tracking. Although GPS has been the most extensively used outdoor localization tool, no standard method exists for indoor localization [1]. Hence, studying indoor localization helps to better understand the complex interactions among the built environment, wireless signals, and human behavior, which can have implications for building design and technology development. However, the constraints and limitations of smartphone-based indoor localization necessitate a comprehensive survey and critical analysis to determine the direction of future research objectives.

This study presents a systematic analysis of the accomplishments attained by previous studies for smartphone-based indoor localization. Apart from listing the motivation for using various techniques in prior studies, this study prescribes some potential directions for future studies to address several identified issues.

This study describes the aspects of indoor localization and the technologies used in the process. While discussing the motivations, challenges, and recommendations linked to indoor localization using smartphones, several gaps were identified. The main contributions of this study are listed as follows:

i. This study presents a systematic analysis of the accomplishments achieved in previous studies for smartphone-based indoor localization by using a systematic review protocol.
ii. This study presents a concise overview of the motivation for using the various techniques in indoor localization as well as the challenges and recommendations that set the path for future research endeavors.
iii. This study presents a substantial analysis section that records crucial information about the sample size of participants, types of walking patterns, sensors, and phone poses that are related to the work.
iv. A list of limitations and future directions is provided for researchers who are interested in exploring walking patterns and recognition.

1.3. Paper Structure and Organization

Overall, this study covers the topic at hand through various aspects and stages, as follows: Section 2 presents information sources, search strategy, study selection, inclusion and exclusion criteria, the article analysis process and the related results, as well as statistical data on indoor localization. Section 3 discusses the technologies applied and the details of data collection. It focuses on studies related to pedestrian activity and evaluation performance. Section 4 describes the substantial analyses based on the reviewed articles. This section presents the reasons for integrating indoor localization into smartphones. Section 5 discusses the most prevalent motivations, issues, and challenges, as well as recommendations for future directions. This study is concluded in Section 6. Figure 1 illustrates the overall structure of this article.

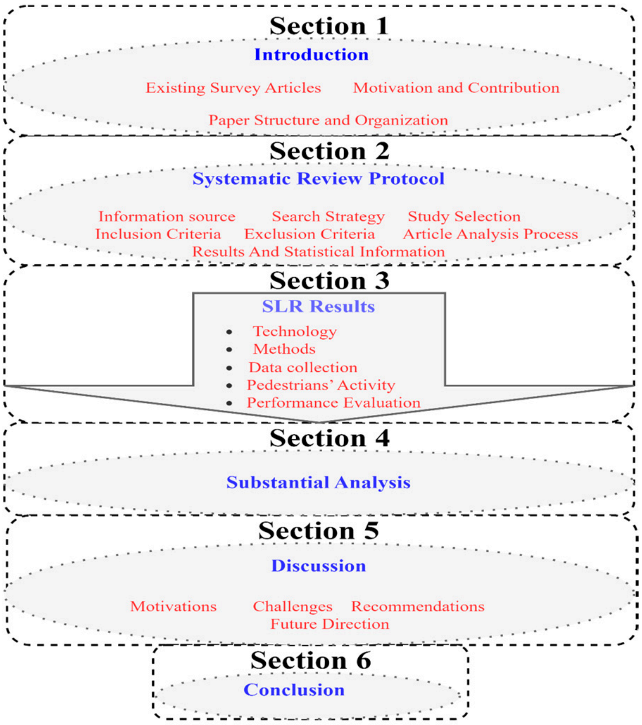

Figure 1. The structure of this article.

2. Systematic Review Protocol

The SLR is a method that systematically determines the literature on a specific topic. This scientific and systematic procedure is used to define, choose, and objectively evaluate similar study samples to collect shards of knowledge from past research work. This SLR procedure is well known for its clear relevance and its ability to incorporate various forms of research methods. The SLR process has many phases, including the selection of a research field, the search method, the research selection criteria, the extraction process, and the synthesis of data. The SLR is deployed to summarize the topic of the article and detect gaps so that new research efforts can be carried out. The protocol used in this study was adopted from [56,57].

2.1. Research Questions

In accordance with the objectives of our study, the following research questions were formulated:

i. What technologies and methods were used in previous studies for indoor localization based on smartphones, excluding marker-based or AR marker-based approaches?
ii. What are the challenges of indoor localization based on a smartphone?
iii. What are the walking patterns and phone poses for pedestrian activity?
iv. What sample sizes were applied in previous studies?
v. What sensor types were used in the experiments in previous studies?

2.2. Information Source

Four digital databases were used to search the related articles. They are: (1) WOS, which indexes research spanning fields in science, social science, and technology; (2) Scopus, which contains abstracts and publications related to various fields; (3) IEEE Xplore, a digital library of technical articles from computer sciences and electrical engineering works; and (4) Science Direct, which contains technical and journalistic papers in highly reliable source journals. The selected databases contain many high-impact research journals that offer extensive insights and scientific integrity, making them suitable for this study.

2.3. Search Strategy

The process of selecting articles published from 2015 to 2022 using the advanced search features found in the four scientific databases (WOS, Scopus, Science Direct, and IEEE Xplore). A combination of keywords in various forms with 'OR' and 'AND' operators in search of relevant articles. The search query is set to ("Indoor location" OR "Indoor tracking" OR "Indoor monitoring" OR "Indoor localization" OR "Indoor localization" OR "Indoor position") AND ("Smartphone" OR "Mobile" OR "Cellular information" OR "Sensors"). The papers were selected after they were analyzed and reviewed during the search and filter processes. In addition, manual search and snowballing [58] were deployed to integrate more studies. Snowballing involves both forward snowballing (looking for relevant articles referenced in a given article) and backward snowballing (searching for relevant articles quoting a given article).

2.4. Study Selection

The analysis started with a simple search that included 4151 papers. The following procedures were applied: discard duplicate papers; scan the titles and abstracts of journals to determine their importance; and read full-text with data extraction from each paper to check if it fit the inclusion criteria. The selected information was entered into the Microsoft Excel sheet during the data extraction process.

2.5. Inclusion Criteria

All the gathered articles were first included in the primary phase of selection by going through the title, keywords, and abstract of each paper. In the secondary phase of selection, the whole article was read, and some articles were excluded based on the following inclusion criteria:

(a) Articles or conference papers published in English-language journals.
(b) The main focus is on indoor localization based on smartphones.
(c) Reviewing and surveying indoor localization techniques to identify location.
(d) Developing indoor localization techniques using smartphone-based systems with related experience.

2.6. Exclusion Criteria

This section discusses the eliminated articles that did not conform to the inclusion criteria (see Figure 2). The following lists the exclusion criteria:

- Articles not written in the English language.
- The publication is either a book chapter or another type of article.
- Duplicate articles.
- Articles unrelated to the topic area and topics that deviate from indoor localization using smartphone-based systems.
- Articles focusing on marker-based or AR marker-based approaches for indoor localization using smartphones.

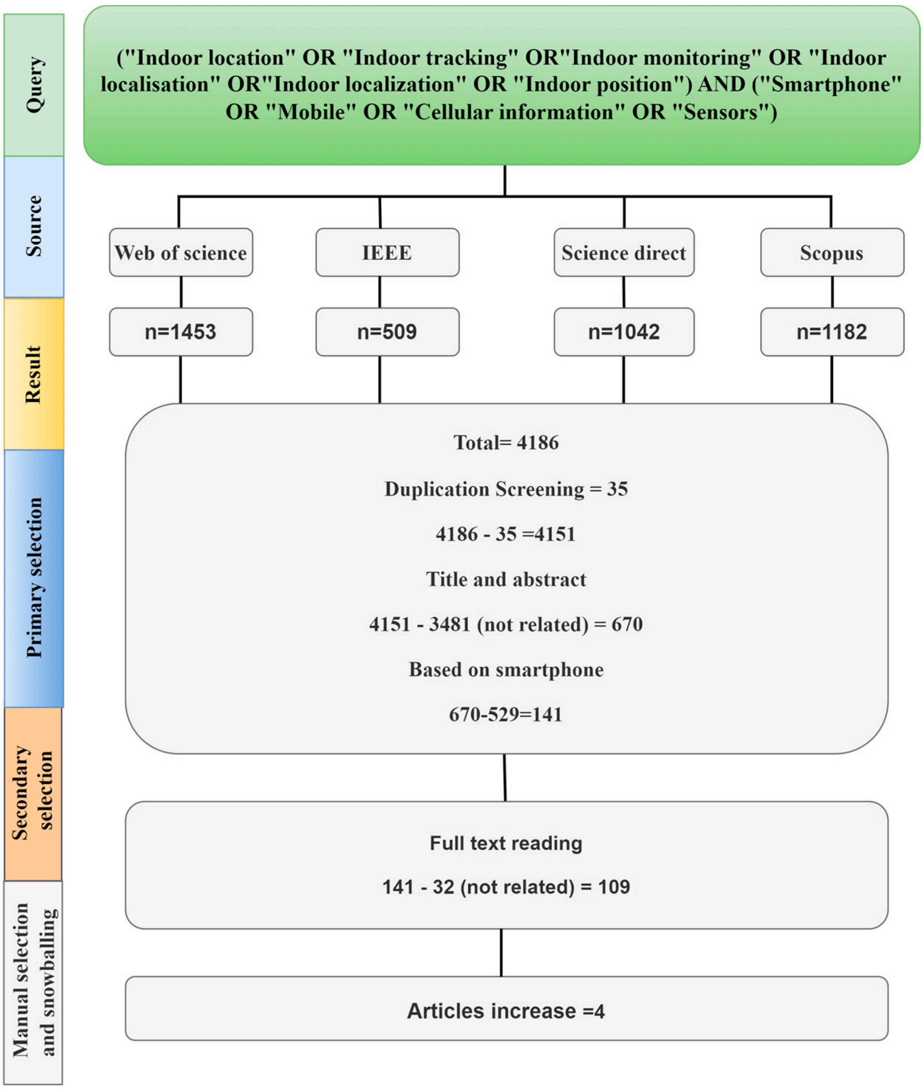

Figure 2. Flowchart of the search query and inclusion criteria for articles selection.

Note that we exclude the articles that describe marker-based approaches that use physical markers, such as printed patterns or codes, that are placed in the indoor environment to help with localization. While this method employs the smartphone camera sensor, it demands users actively scan and recognize the markers, which can be inconvenient and disrupt the navigation experience. Moreover, it may not provide a seamless experience for users. Therefore, our study has excluded articles that utilize markers and AR marker-based methods. Additionally, there is an existing review available that discusses marker-based navigation [55].

2.7. Article Analysis Process

The selected articles were initially categorized in a Microsoft Excel file. The authors reviewed the full text and identified a significant collection of comments regarding the analyzed articles. The key results were compiled, tabulated, and explained. Significant data were saved in Microsoft Word and Excel files, which included reviewed publications, source indices, motivations, challenges, data collection and analysis methods, evaluation criteria, and recommendations.

2.8. Results and Statistical Information

First, 4186 articles were collected (1182 articles from Scopus, 1453 articles from WOS, 1042 articles from ScienceDirect, and 509 articles from IEEE Explore). After the filter process, 35 duplicate articles were discarded. Next, 3481 articles were further excluded after titles and abstracts were checked, leaving only 670 articles. An additional 529 papers were excluded because they focused on smartphones. In the final full-text review, another 32 articles were removed. In total, only 109 articles were found in secondary selection to cover a wide range of subjects and methods related to indoor localization using smartphones. Table 1 shows the selected articles based on the technology used in indoor localization, which includes Wi-Fi, Bluetooth, RFID, acoustic, geomagnetic, and other technologies to provide accurate indoor localization and tracking.

Table 1. Selected articles based on technology.

Type of Technology	Articles
Wi-Fi	[2,6,12–14,17,25,59–92]
RFID	[19,20,93]
IMU	[5,9,15,17,20,27–29,66–73,83,93–102]
BLU	[9,10,18,74,75,82,86,89,92,95,96,103–109]
Geomagnetic	[1,4,76,77,80,82,87,110–117]
Acoustic	[21,22,24,102,102,118,119]

In addition, we found 4 more articles after conducting manual searches and snowballing in different publication datasets such as ACM, Springer, and other databases.

3. SLR Results

Indoor localization is becoming more familiar with the increased use of IoT in modern society. Smartphone-based indoor localization systems overlap in various ways, such as by using the same technology or methods. We categorized the selected articles into 4 categories based on technology, methods, data collection, and activity. Even so, finding an appropriate classification can be difficult. Table 1 shows the overlap between the articles in different categories. Figure 3 illustrates the classification of articles, and a description of each article is provided under its most relevant category. The following subsections explain the articles in each respective category, and a description of each article is provided under its most relevant category.

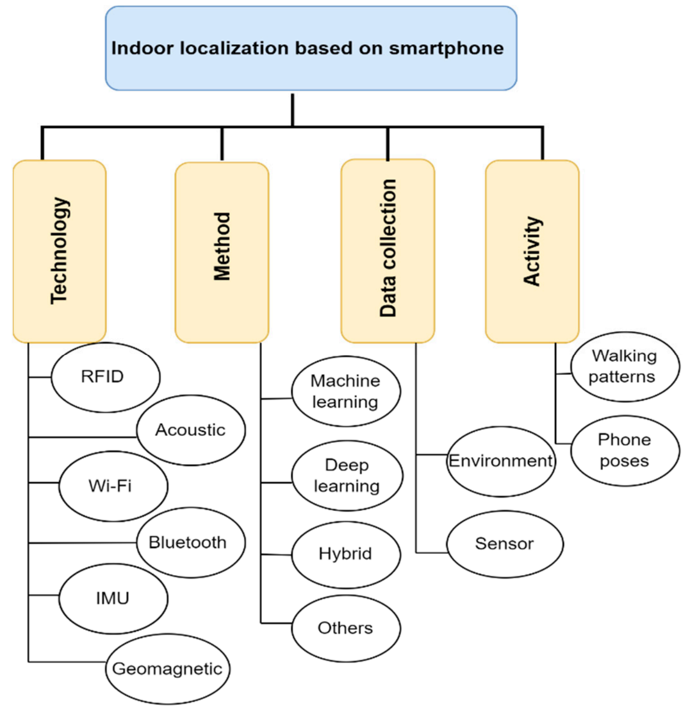

Figure 3. Classification of articles selection.

3.1. Technology

The request for LBS is growing in tandem with the rapid development of devices for mobile terminals and techniques on the internet [120]. However, due to the escalating complexity of indoor constructions and obstacles in indoor settings, the signals are readily blocked, and this exerts multipath effects [14].

Many studies have reported reliable indoor positioning findings. Many techniques can be used for indoor localization, such as wireless local area networks (WLAN) [82], acoustic [102], Bluetooth [95], MEMS [100], geomagnetic [76], RFID [19,20], and other positioning technologies. Both Wi-Fi and PDR have long been recognized as two of the most common indoor localization methods, as they are cost-efficient [70]. Sensor location is flexible with PDR, as sensor precision is not required [28]. Table 2 presents the comparison of indoor localization technologies.

3.2. Methods

Many approaches have been used in varied contexts and applications to classify pedestrians' motion states and phone poses. In the localization process, movement states and phone positions can be integrated and matched at will. Recognition systems use ML approaches to read movement data, learn from the data, and classify movement into patterns based on what they have learned. The ML approaches are preferred when compared to rules-based systems because they assist in solving problems that traditional methods cannot facilitate. By focusing on the results rather than the complete decision-making process, ML is more flexible and resistant to some of the issues encountered in rules-based systems. The Hidden Markov Model (HMM) is particularly well-known for detecting time-varying patterns, such as activity recognition [78,98]. The k-nearest neighbor (KNN) is a commonly used classifier that is simple yet efficient; it has been used to estimate positions using Wi-Fi RSS data [12,76,113]. To categorize the combination modes, support vector machines (SVM) and decision trees (DT) have been applied. The SVM recognizes movement states, while the DT distinguishes between distinct phone positions [99]. To recognize walking patterns, the random forest algorithm (RF) with additional features and classifier proofing (CP) were applied in [15]. The Maximum Likelihood algorithm can revise the moving direction from sensors [73].

Table 2. Comparison of technologies used for indoor positioning.

Technology	Approach	Advantages	Disadvantages
RFID	RSS, Proximity	RFID tags can be attached to items and deployed in harsh locations without requiring line-of-sight communication [19].	RFID is used with localization based on smartphones with external devices, even with limited positioning coverage [20]. RFID is used in a small area and it relies on short-range connection [4].
Acoustic	TDOA, ToA	Acoustic waves have slower propagation speed and are relatively stable, thus the ability to transfer information in an indoor environment effectively [21].	Acoustic waves are frequently reflected or obstructed by walls or other things, thus affecting the performance of the localization system and causing time delay [24]. They have low updating rates and short operating distance [77].
Wi-Fi	RSS	Wi-Fi is widely utilized with indoor localization due to its lower hardware cost and wide-scale coverage [70].	The accuracy of Wi-Fi localization is affected by RSS variations and complicated indoor radio environments [68,70]. Much time and work is needed to construct and maintain an RSS location-direction database, but it cannot handle user mobility [69].
Bluetooth	RSS, Proximity	Small, cheap, light, and low power consumption; Bluetooth is used in smart gadgets [104]. Most smart devices can receive BLE RSS transmissions [103].	Without additional infrastructure, BLE systems cannot function correctly or deliver the localization precision required for indoor LBS [40].
IMU	Tracking, navigation	low in cost, small in size, and low in power consumption, The error rate of a PDR system is reduced when IMU incorporated in smartphones is used [28]. Sensor placement flexibility and low sensor accuracy are vital when using IMUs in smartphones [8,28].	Drift errors can build over time, which can result in significant errors in the estimated position and orientation of the device [68]. The navigation accuracy IMU can decrease with time due to noise that causes drift [79,102].
Geomagnetic	RSS	The Earth's magnetic field is homogeneous for small areas (a few meters), pervasive, cheap, infrastructure-independent, and stable time wise [40].	Anomaly readings can be caused by fluctuating measurement readings and the vicinity of ferromagnetic elements, such as iron and nickel [40].

Deep learning (DL) is an ML approach that consumes more time to train because it requires a huge amount of data, while ML takes less time and demands less data. Deep learning algorithms are organized in layers to form an NN capable of self-learning and making intelligent decisions. The use of an artificial neural network (ANN) yields more accurate results than conventional ML approaches [115]. Convolutional neural networks (CNN) are extremely effective at extracting abstract features, particularly in picture recognition. Many researchers adopted CNNs for gait or activity recognition due to their ability to recognize features [1,30,121].The researcher in [26] used a deep learning model that combines Wavelet and CNN, which can fully utilize the complicated data streams from smartphone sensors, effectively extract multidimensional features, and accurately recognize pedestrian activities. Long short-term memory (LSTM) [91,111] and bidirectional long short-term memory (BLSTM) [122] are appropriate to deal with time series data and capture long-term dependencies in the data series. Furthermore, CNN and recurrent neural networks (RNN) are commonly used to identify walking patterns based on numerous sensor data from smartphones [100]. When the device position is changed, the localization accuracy suffers [4]. The recognition system based on deep learning described in [32] must be trained with more datasets before it can be generalized to model indoor activity. Moreover, there are other different methods that can be used in the localization process. Table 3 illustrates some benefits of using various methods.

Table 3. Motivations for using the method in previous studies.

Ref.	Type of Approaches	Methods	Motivation
[78,98]	ML	HMM	A statistical prediction model that can estimate probabilities of observable cases. HMMs are well-known for recognizing patterns that change over time and have applications in pattern recognition, motion detection, and speech synthesis.
[1,12,75,76,113,123]	ML	KNN	A popular classifier with a simple yet efficient structure. This method is adopted to estimate the location of the sample with the closest feature distances. A modified (KNN)Is exhibited to determine the pedestrian's current location.
[99,124]	ML	SVM	A model for classification that can process nonlinear relations and is utilized to identify patterns of behavior that frequently occur during indoor navigation.
[99]	ML	DT	A non-parametric classification algorithm with a tree-based representation that can accurately reflect the characteristics of the data.
[15]	ML	RF	A method that requires less training time, offers high precision, and promotes simplicity, thus suitable for recognition systems.
[28]	ML	GDA	Gradient descent algorithm reduces heading drift by combining inertial data with only a subset of reliable magnetometer data.
[115]	DL	ANN	A method that can learn and model complex, non-linear relationships. It can produce more accurate results than traditional machine learning techniques.
[1,30]	DL	CNN	A method effective in extracting features used in activity or gait recognition that can automatically learn appropriate features by combining feature extraction and classification with a neural network and can learn a non-linear relationship between feature vectors.
[100]	DL	RNN	An appropriate model to address time series data and significantly reduce the complexity of increasing parameters. It is ideal for automatic nonlinear feature extraction.
[111]	DL	LSTM	It is appropriate for dealing with time series data and capturing long-term dependencies in the data series. The hidden LSTM units can exploit temporal information in a magnetic field and light intensity data by recursively mapping the input sequence to the output label.

Table 3. *Cont.*

Ref.	Type of Approaches	Methods	Motivation
[4]	DL	NNs	NNs can play an essential role in minimizing the influence of heterogeneity of devices and improving indoor localization accuracy
[100]	Hybrid	Multiscale CNN-RNN	A model used to invert the effect of the CNN's automatic feature extraction.
[21]	Hybrid	LSTM-RNN	The specific cell unit and gate structure can retain updated information from previous moments via loop feedback connection, thus making them widely appropriate for artificial disturbance reduction.
[122]	Hybrid	CNN-BLSTM	A technique used to obtain multi-layer features from a hybrid CNN/BLSTM network and to improve the recognition of human complicated activities.
[87]	others	GraphSLAM	The system automates this signal map creation method by considerably decreasing survey overhead.
[2]	Others	SFM	Based on a multi-constrained image-matching method, an SFM (Structure from Motion) based algorithm is developed to estimate heading angles and reconstruct trajectories.
[6]	Others	Trilateration method	A method may be used on any hardware platform and requires no additional hardware or infrastructure.
[8]	Others	map-matching	A map-matching method based on particle filters is used to handle the problem of predicted pedestrian paths travelling through building walls
[3,9,10,17]	Others	PDR	The method avoids the PDR cumulative error problem while mitigating the impact of RSSI oscillations and instability encountered in indoor situations.
[12]	Others	ScHS	To enable real-time synchronization, the step-constrained hybrid synchronization (ScHS) method employs an online Dynamic Time Warping (DTW) algorithm and a modified (DTW) method to calibrate alignment drift. It achieves consistent and accurate synchronization of two signals.
[13]	Others	WPL	The weighted path loss (WPL) method is more appropriate than the popular fingerprinting approach, which involves manually gathering a large dataset for training.
[63,73]	Others	Maximum Likelihood	The Maximum Likelihood estimate is used in indoor localization to determine the user's location.
[125]	Others	backtracking approach	It is used to undo incorrect correction decisions and review previous user trajectory measurements to determine the most likely current location of the user.
[93]	Others	PDR with Particle Filter	The technology provides long-term precise and reliable tracking and is drift-free
[105]	Others	PDR with Kalman filter	To create a strong and precise indoor localization system, which was then used to estimate key important parameters of the PDR technique.

3.3. Data Collection

The data collected by a smartphone or AP, such as Wi-Fi and Bluetooth, can be applied to detect the user's location. A smartphone has various sensors, including a light sensor, camera, accelerometer, magnetometer, gyroscope, and barometer, stemming from the progress of sensing technology. In order to detect walking patterns as well as estimate the position and orientation of an object, data from the smartphone's built-in sensors or access points (APs) or both can be applied [2,32]. Most smartphones have IMUs built-in (accelerometer, magnetometer, and gyroscope) to capture people's movement. The accelerometer measures acceleration values along three axes (x, y, and z). The values are used to calculate the distance traveled by the smartphone and to determine the user's actions [3]. An accelerometer is used to acquire information about the user's gait and step length, as well as to construct sensor reading selection rules based on the actual environment and the real-time features derived from magnetometer and gyroscope sensors [120]. The rotation rate of the device's three axes is measured by using the gyroscope sensor [126]. Since the accelerometer cannot handle rotations, it is necessary to integrate it with a gyroscope to identify movement direction. The direction adheres to the device's coordinate system [3]. The magnetometer determines the device's orientation to the Earth's magnetic north, and it serves as a digital compass (e.g., displaying the user's current location in navigation applications). Thus, one may employ a combination of an accelerometer, gyroscope, and sometimes a magnetometer to determine the user's stride length and movement direction, thus making it suitable for pedestrian tracking [82]. The pedestrian's heading is determined by using a combination of magnetometer and gyroscope sensor information [27]. Magnetic and light sensors can be integrated for interior localization in closed areas without ambient light [111]. To move into the third dimension, several localization systems use a barometer. When utilizing the elevator/escalator and walking up the stairs, both the accelerometer and barometer can be used to monitor pressure changes with altitude [98], hence providing continuous updates with every incoming barometer reading. Table 4 presents an overview of the references and characteristics of indoor localization data collection, which include different techniques, various sensors, and multiple sample coverages. The studies were conducted in offices, universities, and shopping malls with different coverage sizes.

Table 4. The characteristics of indoor localization data collection.

Ref.	Environment	Technology	Sensor	No. of AP	No of Participants	Test Coverage Space
[59]	Campus buildings	Wi-Fi	N/A	N/A	N/A	1000 m^2 1200 m^2 1500 m^2
[65]	University	Wi-Fi	N/A	64 AP	N/A	N/A
[66]	Engineering Buildings Tunnel system	Wi-Fi, IMU	Acc, Mag, Gyr	33 AP	N/A	N/A
[67]	Museum.	Wi-Fi, IMU	Bar, Acc	42 beacons	N/A	2500 m^2
[68]	Office	Wi-Fi, IMU	Acc, Gyr, Mag	11 AP	N/A	11 m by (12.4 m/ 10 m) by 3 m
[61]	N/A	Wi-Fi	N/A	6 AP	N/A	15 by 5 m
[69]	Shopping malls	Wi-Fi, IMU	Gyr, Acc	50 AP	1	119,685 m^2
[70]	Office	Wi-Fi, IMU	Acc, Gyr, Mag	8 AP	N/A	43.5 m by 11.2 m
[14]	Office	Wi-Fi	N/A	5 AP	N/A	183.68 m^2
[71]	Rectangular motion Linear motion Corridor	Wi-Fi (RSSI), &IMU	Acc Gyr, Mag	4 AP	1	45 m by 37 m. 75 m by 3 m
[72]	Office room	Wi-Fi, IMU	Acc, Gyr, Mag	4	4	N/A
[63]	University	Wi-Fi	N/A	20 AP	N/A	80 m by 40 m
[73]	Office Shopping center Hall	Wi-Fi, IMU	Acc, digital compass	103, 25 and 35 AP	N/A	90 m by 10 m 115 m by 25 m 50 m by 15 m

Table 4. *Cont.*

Ref.	Environment	Technology	Sensor	No. of AP	No of Participants	Test Coverage Space
[106]	Indoor corridor and office	BLU	Acc, Mag	12 beacons	N/A	42.2 m by 21.0 m
[8]	2D paths in indoor corridor. 3D paths, six flights of stairs, and four sets of horizontal trajectories	MEMS	Acc, Mag, Gyr, Bar	N/A	5	Corridor at 92.46 m length with four 90 degree turns. The walking distance was 174.63 m. The estimated walking distance in 3D space was 363.22
[94]	Office	IMU	Acc, Gyr, Bar, compass	N/A	3 2	365 m 345 m
[17]	University	Wi-Fi, IMU	Acc Mag	4 AP	1	30 m by 20 m
[77]	University	Magnetic, Wi-Fi	Acc, Mag	242 AP	N/A	13.4 m by 6.4 m
[28]	University	IMU	Acc, Gyr, Mag	N/A	1	37.80 m 452.00 m 858.00 m
[27]	University	IMU	Acc, Mag, Gyr	N/A	1	N/A
[96]	University	BLE	Acc, Mag	8 Beacon	N/A	25 m by 15 m
[23]	Institute of Science and Technology	IMU	Acc, Mag, Gyr	N/A	5	168.55 m
[15]	University	IMU	Mag, Acc	N/A	8	N/A
[98]	Office Shopping mall.	IMU	Acc, Gyr, Mag, Bar	N/A	4	52.5 m by 52.5 m 80 m by 60 m
[82]	University	BLU, Wi-Fi	Acc, Gyr, Mag, Bar	N/A	N/A	145 m to 260 m
[99]	Office	IMU	Acc, Gyr, Mag	N/A	10	700 m
[30]	N/A	IMU	Acc, Gyr, Mag	N/A	77	N/A
[32]	N/A	IMU	Acc, Mag, Gyr, Bar	N/A	10	N/A
[100]	N/A	IMU, GPS	Acc	N/A	9	60 m
[104]	Office	BLU	N/A	20,8 beacons	N/A	60 m by 40 m
[29]	University	IMU	Acc, Gyr, Mag, Cam	N/A	5	207 m
[1]	University	Magnetic	Acc, Gyr Mag, Cam	N/A	N/A	90 by 36 m^2
[10]	Office Straight corridor Multi path	BLE	Acc, Gyr,	N/A	5 15	10 m 124 m 100 m
[97]	University	IMU	Acc, Gyr, Mag, Cam	N/A	6	106 m 207 m
[93]	Rooms Corridor	RFID	Acc, Gyr	N/A	10	N/A
[101]	office	IMU	Acc, Gyr, Mag	N/A	3	18 m by12 m

Table 4. *Cont.*

Ref.	Environment	Technology	Sensor	No. of AP	No of Participants	Test Coverage Space
[127]	N/A	Magnetic	GPS, Acc, Bar, light,	N/A	15	200 m by 200 m
[128]	Office	MEMS	Acc, Gyr, Mag	N/A	4	124 m^2
[129]	Corridor	MEMS	Acc, Mag, Gyr, Bar	N/A	3	118 m

AP: Access point, **Acc:** Accelerometers, **Gyr:** Gyroscopes, **Mag:** Magnetometer, **Bar:** Barometers, **GPS:** Global Positioning System, **Cam:** Camera, **BLE:** Bluetooth, **N/A:** Not available, **MEMS:** Micro-electro-mechanical systems.

3.4. Pedestrian Activity

The pedestrian activity mode can be categorized into walking patterns and phone poses based on the daily activity of the pedestrians and the poses of using a phone.

3.4.1. Walking Patterns

Walking pattern recognition is significant for various usages, such as navigation, medical diagnostics, elderly assistance, emergency service servicing, monitoring systems, and indoor localization for pedestrians [30]. Walking patterns can be applied to detect the activities accrued by a person based on sensory data to learn the context in which the activity occurred [36]. The different types of walking patterns are [32]: ambulation (e.g., walking, running, sitting, standing still, lying, stair climbing, and taking the escalator/elevator) and transmission (e.g., taking a bus, cycling, and driving). Various sensors can detect movements, including gyroscopes, magnetometers, and barometers, which are frequently employed in conjunction with the accelerometer for activity detection [32,82]. In the case of inertial sensor-based localization, the distance can be calculated by calculating the number of steps taken by the user. Localization accuracy is determined by the user's walking pattern, speed, and step lengths, which differ from one person to another [69]. Walking pattern recognition enables precise estimation of the number of steps taken and the length of each step, the two most important aspects of PDR. The rationale for the number of steps is that while a user is walking, the accelerations display periodic and repetitive patterns [130]. Localization accuracy in PDR is directly influenced by the precision of step counting and the step length estimate.

3.4.2. Phone Poses

Phone pose refers to a stance in which one holds or places a phone, such as holding, calling, swinging, and pocketing. Since carrying positions can directly affect settings for step recognition and step length estimation, it is critical to determine the carrying position of smartphones. Many researchers have studied PDR by using handheld smartphones [28,100]. Handheld-PDR is a method of capturing pedestrian positions and headings using handheld mobile devices. It consists of step detection, stride length estimation (SLE), and heading determination. Nevertheless, the existing algorithms have some limitations, as many localization systems assume that the heading angle offset (the angle between smartphone direction and pedestrian direction) remains constant [99]. This constraint limits localization systems in smartphones, which offer unrestricted carrying positions and rotations. However, phone pose is arbitrary during localization, while heading offset may not be fixed. Table 5 presents studies that focused on the different types of walking patterns and phone poses. Most of the studies examined walking and climbing stairs as the walking patterns but neglected elevator movement. Therefore, it is critical to recognize the movement of a user moving across different levels in a building. As for phone posing, most of the studies assessed objects in hand and in pocket for their experiments.

Table 5. Walking patterns and phone poses.

Ref.	Walking Patterns											Phone Poses						
	Standing	Walking	Door (Pushing, Pulling)	Looking Around	Running	Satir (Up, Down)	Elevator (Up, Down)	Escalator (Up, Down)	Turning	Jogging	Jumping	In Hand	In pocket	Calling	Texting	Swinging	portable Desk	In Front
[59]	-	√	-	-	-	-	-	-	-	-	-	√	-	-	-	-	√	-
[65]	-	√	-	-	-	-	-	-	√	-	-	√	-	-	-	-	-	-
[66]	-	√	-	-	-	-	-	-	√	-	-	√	-	-	-	-	-	-
[67]	√	√	-	-	-	√	-	-	-	-	-	√	-	-	-	-	-	-
[68]	-	√	-	-	-	-	-	-	-	-	-	√	-	-	-	-	-	-
[69]	-	√	-	-	-	-	-	-	-	-	-	√	√	√	-	√	-	-
[71]	-	√	-	-	-	-	-	-	-	-	-	√	-	-	-	-	-	-
[8]	-	√	-	-	-	√	-	-	-	-	-	-	√	-	-	-	-	-
[15]	√	√	-	-	√	-	-	-	-	-	-	√	√	-	-	-	-	-
[100]	-	√	-	-		-	-	-	-	-	-	√	√	-	-	√	-	-
[99]	-	√	-	-	√	√	-	-	-	-	-	√	√	√	-	√	-	-
[101]	-	√	-	-	√	-	-	-	√	-	-	√	√	√	√	-	-	-
[32]	√	√	-	-	√	√	√	√	√	-	-	-	-	-	-	-	-	-
[12]	-	√	-	-	-	√	-	-	√	-	-	√	-	-	-	-	-	-
[129]	-	-	-	-	-	√	-	-		-	-	√	-	-	-	-	-	-
[31]	√	√	√	√	-	-	-	-	√	-	-	-	√	√	-	√	-	√
[131]	√	√	-	-	-	-	-	-	-	-	-	√	-	-	-	-	-	-
[130]	-	√	-	-	-	-	-	-	-	-	-	√	-	-	-	-	-	-
[26]	√	√	-	-	-	√	-	-	-	√	√	-	-	-	-	-	-	-

"√": shows that the contexts are covered, **"-"**: shows that the contexts are not covered.

3.5. Performance Evaluation

Variance matrices are used in indoor localization systems to assess performance. The performance efficacy of the classification models was assessed using variance matrices (e.g., accuracy, confusion matrix, precision, recall, F-score, and error rate). The following parameters are utilized in the evaluation criteria:

1. Accuracy is measured at the macro level for multiclass classification processes using confusion matrix results. It refers to how close or how far a given collection of measurements is to its true value [true positive (TP) + true negative (TN))/(TP + TN + false positive (FP) + false negative (FN)] [100].
2. Precision denotes the proportion of accurately predicted conditions to the total positive outcomes expected for each class, TP/(TP + FP) [100].
3. Recall refers to the ratio of accurately predicted positive conditions to all true conditions for each class, TP/(TP + FN) [100].
4. The F-score is a measure of the overall performance of a classification model by measuring the harmonic mean of its precision and recall, 2 × (precision × recall)/(precision + recall) [100].

5. The confusion matrix as the classification class value distinguishes the incorrect and correct predictions from the actual results of the test sample. It is represented by four expected outcomes: TP, TN, FP, and FN [100].
6. Time complexity is critical when assessing the performance efficiency of a system. The optimal classifier achieves the least time complexity while maintaining the highest accuracy [125].
7. The error rate calculates the errors of a classification model for each dataset group. The best classification result is described based on the error rate measure on the training and validation sets, which refers to a low error rate for an accurate classification model [97].

4. Substantial Analysis

This section presents a critical analysis of past work. Data were derived from studies on indoor localization-based smartphones. Figure 4 summarizes the data by choosing subsets related to indoor localization systems based on four parts: sample size, walking patterns, phone poses, and sensor types.

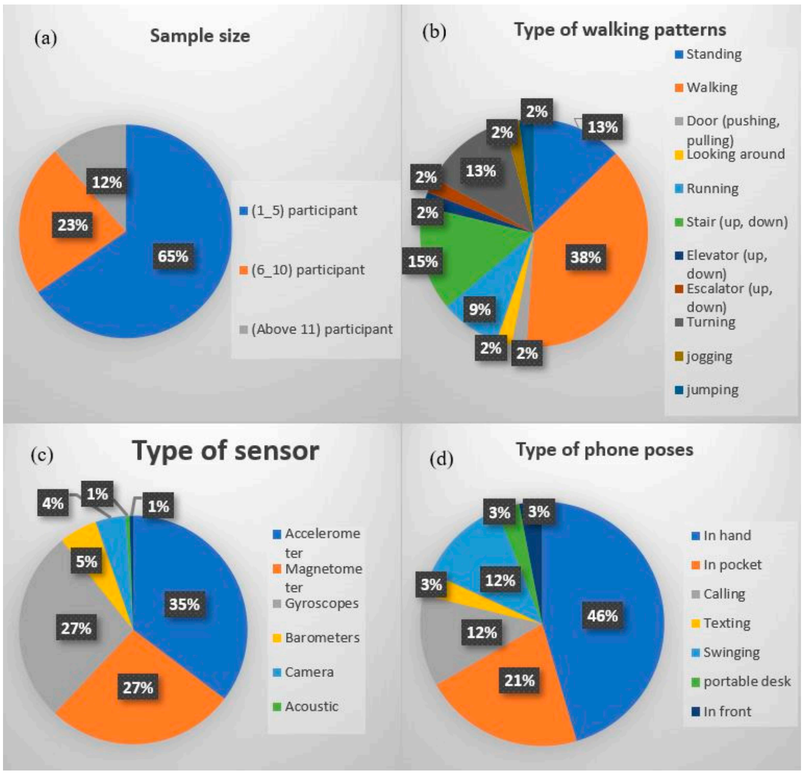

Figure 4. Percentage of aspects identified in past studies: (**a**) sample size, (**b**) walking patterns, (**c**) sensor types, and (**d**) phone poses.

The sample size in Chart (a) displays three groups. Group (1) includes studies that used 1–5 participants, while group (2) consists of studies that used 6–10 participants, and group (3) examined more than 11 participants. About 65% of the studies used a sample size of 1–5 participants, mainly because a large number of participants consumes a lot of time and money. Deploying a smaller number of participants can keep costs and time requirements manageable. Indoor localization studies are complex, and controlling the environment can be difficult. A small number of participants eases environmental control and ensures that the study is conducted under consistent conditions. Next, 23% of the studies deployed 6–10 participants, while 12% of studies employed more than 11 participants. Moving on, chart (b) illustrates the walking patterns. Most of the studies identified normal walking (38%), followed by stairs (up, down) (15%), running and turning (13%), standing (13%), as well as elevators (up, down), escalators (up, down), doors (pushing, pulling), jogging, jumping, and looking around (2%). In Chart (c), the most common type of sensor applied in prior studies was an accelerometer (35%). This was followed by the magnetometer and gyroscope (27%), barometer (5%), and cameras (4%), as well as the acoustic and GPS at 1% each. These percentages were collected based on all articles. Chart (d) displays several phone poses reported in past work. In 46% of the trials, the participants held their phones in their hands, while 21% had their phones in their pockets, 12% were swinging and calling their phones, and 3% were in texting mode, on a portable desk, or in front of them.

5. Discussion

The literature data on indoor localization were compiled in this study. The following subsections present three important aspects: (1) motives and benefits of using indoor localization; (2) challenges related to the current direction; and (3) recommendations to address the challenges in future studies.

5.1. Motivation

This section presents parts of the literature that have encouraged and motivated the integration of indoor localization into smartphones. The identified motivations are categorized based on their general purpose and similarities. An overview of the motivations is illustrated in Figure 5.

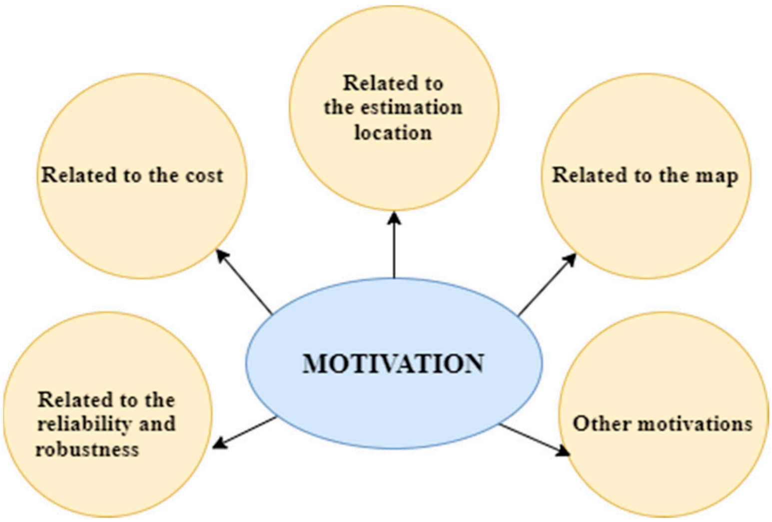

Figure 5. Overview of motivations.

5.1.1. Motivation Related to Reliability and Robustness

The five aspects grouped under the reliability and robustness category are reliability, accuracy, walking patterns and smartphone holding, coverage, and fusion methods. These aspects are explicated in the ensuing subsections.

a. Reliability

Researchers were motivated to improve aspects of accuracy and reliability by integrating Wi-Fi with PDR [65] or by using the fusion algorithm [28,70]. The PDR can be applied without relying on external infrastructure, thus its ability to facilitate the integration of LBS [29,97]. The magnetic field method is considered good as it promotes efficiency and reliability, which are the most immune to pre-installed infrastructure [8,111,117]. Although sensors are becoming more trustworthy to date [110], scholars are looking for additional ways to detect more reliable and energy-efficient indoor positioning due to the prevalence of smartphones [66]. Hybrid indoor localization and navigation can deliver perfectly accurate localization and tracking performance with good precision [93]. To improve position accuracy and enhance operating time, average modes can be used to process the heading angle data [5]. It is also crucial to look into the Wi-Fi round-trip time range and RSS to ascertain the robustness of the positioning system [25].

b. Accuracy

Many studies were motivated to enhance localization accuracy [3,8,71,73,95] for dead-ending handling issues [94] or to locate a single tagged object [19] or to achieve stable performance in the tracking process [64]. In order to improve accuracy, there must be a dataset that offers RSSI in a variety of settings and device configurations, along with the precision of location points [81], because it offers acceptable accuracy in office buildings with Wi-Fi access points [17]. However, RSS fingerprint positioning technology dismisses a huge amount of parameters from estimation [63,124]. The smartphone-based acoustic approaches are used to improve indoor tracking performance by increasing the precision of position estimates [102] or by combining the horizontal and vertical (HV) magnetic fingerprinting model with the magnetic density fingerprinting model [113]. The indoor localization technique based on channel state information is widely used due to its excellent processing performance and better localization accuracy [124]. The method enhances overall location accuracy, especially in areas where anchor nodes are limited [20], by using particle filter formulation, estimates of PDR movement, and map data [113]. Finally, both PDR and RSS methods have been deployed to achieve accuracy through absolute positioning, drift error reset [10], or by resolving errors in step length estimates and heading determination [101]. Localization performance can be enhanced via multipath error by separating the signals into low- and high-quality signals [61].

Indoor localization using inertial sensors requires fine layout maps to set restrictions and markers that limit error drift. This demands improved IMU measurements to compensate for errors generated by off-the-shelf IMUs and magnetic field disturbances [64]. The drift errors caused by sensor readings could be influenced by their surroundings [120]. Heading drift can be reduced by combining inertial data with only a portion of magnetometer data [28]. Next, PDR errors can be minimized by using visible light positioning (VLP)-assisted smartphone-based PDR technology [5], combining Wi-Fi and PDR localization with an extended Kalman filter [83], or decreasing the drifting effects produced by the user's walking pattern [17]. Additional data are included for location estimation to limit the number of errors that may accumulate in the localization due to various sensor errors [82]. The distance between beacons and a mobile device can be estimated by using PDR or filtering algorithms to improve tracking or minimize positioning mistakes [103]. Therefore, PDR can be combined with other methods to reduce errors [72].

c. Walking patterns and smartphone holding

Several researchers analyzed walking patterns and phone poses due to their significance. Walking patterns are identified to detect the activities accrued by a person based on sensory data to learn the context in which the activity occurs. When a user enters a building, the direction of movement and distance are estimated [3], regardless of gait, position, smartphone direction, and pedestrian tremor [100]. The accuracy and adaptability of the PDR system are affected when pedestrians move in different states and hold their smartphones in different positions [99]. Moreover, higher SLE accuracy is achieved with an enhanced SLE model for varied walking patterns [15].

d. Coverage

The literature is handicapped by coverage, thus motivating researchers to enhance coverage, location update rate, and extended coverage without sound trouble [119]. Localization based on the detection of beacons covers the navigation region and does not necessitate precise parameter estimates [114]. Hence, it is vital to provide a robust fused localization system that can withstand extreme environments (poor coverage of RSS, change of device position, etc.) [74]. When the density of WAP is limited, tracking smartphones in indoor locations becomes difficult [17]. The increasing number of wireless transmitters in indoor locations helps in developing an accurate and reliable indoor localization system [116].

e. Fusion methods

Many studies have focused on several location-based indoor tracking solutions to enhance localization accuracy and performance in real-time. Many have improved localization accuracy by using Wi-Fi fingerprinting [14,84]. Combining a WiFi signal and camera allows for extracting distance data at a relatively low cost and without the use of a special device [132]. As well as fused Wi-Fi and PDR [13], Bluetooth and ZigBee with a filter based on Wi-Fi [89], crowd-sourcing and ambient sensing [80], as well as mobile device inertial sensors and RSS from BLE beacons [108]. Optimization of the fingerprint approach introduces a feature vector that specifies the reference point, which comprises weight, RSS, and near-beacon rank [96]. Another method that differs from other RSSI-based indoor positioning methods is the use of a new model to adjust for the wireless signal by considering population density, distance, and frequency [88].

5.1.2. Motivation Related to Cost

The three aspects related to motivation in terms of cost, however, are infrastructure, computational cost, and time, as well as technologies. These aspects are explained in the following subsections.

a. Infrastructure

A perfect system should not require additional infrastructure costs or a costly device or system. Wi-Fi-based indoor localization has become a study hotspot due to its cost efficiency and ease of technology application without extra hardware [60,124]. Since the magnetic field is less susceptible to variations in the indoor substructure without requiring an extra localization sensor [1], the smartphone or tablet can be equipped with a magnetometer that is as cost-efficient and high-resolution as the receiver [114]. Smartphone-based PDR with VLP demands only a smartphone and an LED, which are available in most locations [5]. However, the pedestrian tracking systems depend on Smart PDR. Sensors in smartphones are simple, inexpensive, and have low infrastructure maintenance [110], such as IMUs [28].

b. Computational Cost and Time

The computational cost of a model must be low for the performance to be considered good. Low enough is based on a comparison with known solutions. The PDR performance can improve if two essential spatiotemporal gait factors (heel strike and step length) are accurately estimated, which allows for good results at a minimal computational cost [10]. The sensor fusion system can be developed at a low cost, be less intrusive, and have higher mobility and portability [18]. Reducing computational costs by reducing the search space for reference points with affinity propagation clustering [96,133] is viable due to its low cost and easy availability, thus making Wi-Fi-based indoor localization receive much attention [78]. On the other hand, the time is shortened to locate multiple tagged objects [19]. The PDR system supported by a hybrid orientation filter has a simple architecture and low processing complexity [29]. The cost gained from the positioning system can arise from the consumption cost. Meanwhile, BLE has massively decreased energy usage [75,103], is easy to deploy without an active power supply, and has wide support [9].

c. Technologies

Several techniques that affect indoor localization, such as Wi-Fi and Bluetooth, which are often present in smartphones, can offer a low-cost alternative to wireless-based location technologies [86]. Database updates can be performed regularly using crowdsourcing without incurring any survey costs [79]. The RFID indoor localization system (RILS) was introduced to increase efficiency and reduce costs [19]. Another method, a visual-based approach, can be used to lower the cost of human labor, thus its noted applicability in wide interior areas [2]. A microphone sensor is inexpensive and can increase accuracy due to the low transmission speed of acoustic impulses [119]. The smartphone camera can be employed as an additional sensor that can help the visually impaired user identify paths while also providing direction estimations to the tracking system [131].

5.1.3. Motivation Related to Location Estimation

Some researchers were motivated to study the issues of reliable location estimation [82,127], as well as the distance between the target and BLE beacons [104]. Both Bluetooth and Wi-Fi data offer positions that are subject to some level of noise [86]. However, PDR displacement estimation can be used to improve the real-time heading prediction in PDR, identify Wi-Fi FTM outliers [68], and recognize the appropriate locations for placing APs and making announcements for indoor buildings [62]. Acoustic-based indoor pedestrian tracking (IPT) has been proven superior in localization and direction-finding [102]. To estimate the initial location in indoor localization, the trilateration technique was proposed in [96]. The Bayesian ML strategy was proposed to retrieve a user's initial location and movement direction information [73].

For indoor localization based on a smartphone, Wi-Fi and magnetic field information were used in [77] when the sensor node placements were unknown [24]. A unique crowdsourcing method was deployed to deliver an accurate Wi-Fi location solution at a low cost while maintaining the Wi-Fi database [79]. The method can reduce the time taken to obtain fingerprint databases and improve positioning efficiency [84]. To process the uncertainty of position measurements, fuzzy logic techniques are frequently used [107] by employing magnetic calibration, recognizing users' spatiotemporal co-occurrence, and determining their locations [80]. This method can be used to detect patients' exact locations in real-time at their homes [18].

5.1.4. Motivation Related to Map

The main hurdle to fingerprint localization success is obtaining a fingerprint map for a given indoor setting. A site survey was carried out to create a fingerprint map by considering the importance of indoor corners in movement trajectory analysis [11]. Next, a visual-based approach was proposed in an anonymous indoor to create a radio map [2]. The fingerprint-based smartphone localization can be used to develop a more efficient signal map by using GraphSLAM (simultaneous localization and mapping) to reduce survey overhead [87]. Next, a scene recognition model can recognize different floors and increase interior localization accuracy [1].

5.1.5. Other Motivation

This part highlights motivation that does not match with other motivation groups. To estimate the initial position in indoor localization, the trilateration method is proposed in [96]. The fusion results of Bluetooth RSS and PDR can be used to localize the initial position of a smartphone and then track its trail [106]. To mitigate the impact of the initial point estimation error in PDR, landmarks with unique patterns were used as smartphone sensor data [13]. The most important factor in implementing LBS is determining the accurate real-time location of the user [82] and enabling accurate location estimation [69].

5.2. Challenges

Indoor localization seems to pose many challenges. The literature has addressed several issues in many significant respects. This section discusses the most prevalent issues highlighted in the literature regarding indoor localization. An overview of the identified challenges is presented in Figure 6.

5.2.1. Challenges Related to Accuracy

The two aspects related to the challenges of accuracy are the environment as well as smartphones and technologies. These aspects are elaborated on in the following subsections.

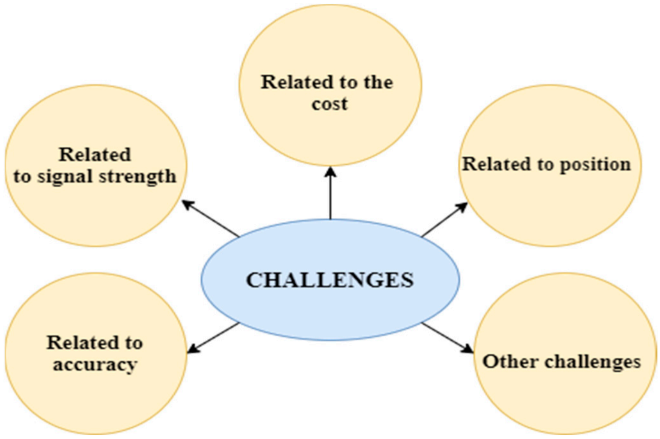

Figure 6. Overview of challenges.

a. Environment

Accuracy remains a primary challenge in indoor environments [59], such as with GPS, which does not work inside buildings [66] due to quality degradation [23,105], GPS indoor localization error, and poor coverage for a vast space [115]. Accuracy is greatly affected in indoor environments, mainly because GPS signals are blocked by obstacles (e.g., buildings) [112,114]. When moving from a GPS-clear outdoor area to an internal setting, the user must be able to continue navigating without interruption [134]. However, ultrasonic signals can be easily blocked by mobile obstacles due to their physical features that constantly cause reflection and multipath problems that lower tracking accuracy [102]. Finally, localization accuracy cannot be guaranteed when the indoor map is difficult to calibrate [12].

Indoor tracking accuracy is still a major issue in applications [18,28,63,73,103,105,108,125,135] due to issues in capturing signals [29]. As a result of information fusion, dependable and exact indoor localization services can be provided [10] to achieve good position estimation accuracy [27].

b. Smartphone and technologies

A challenge related to smartphones is low accuracy in positioning [74]. For instance, a smartphone camera's localization accuracy depends on how quickly the user's direction changes. Many smartphones can give equivalent performance, but localization accuracy is impaired. Although magnetic field-based localization systems offer a good level of accuracy, their performance is often affected by the use of the large variety of smartphones that are available at present. Smartphone companies install magnetometers from various vendors that offer different levels of noise tolerance and sensitivity, which can severely limit the full potential of such systems [115] and cause magnetic deviation [109]. The sensors in a smartphone can be used for indoor localization. The navigation accuracy of MEMS sensors can decrease with time due to noise that causes drift [79,102]. In most cases, environmental and/or wearable sensors are required to increase stability, which can be both costly and inconvenient [3]. Localization accuracy can be affected by cumulative errors due to MEMS sensors' limited precision [128]. Finally, sensor drift leads to bad performance in conventional tracking systems based on PDR [97]. Meanwhile, reachable positioning accuracy with BLE beacons is still unacceptable for some real-world applications [10].

In Wi-Fi technology, the problem of device diversity arises when multiple devices in the same location have different Wi-Fi fingerprints [90]. The vast range of Wi-Fi hardware modules and software stacks applied in smartphones introduces errors that can affect localization accuracy [78]. The high cost and poor performance of typical planar maps make Wi-Fi fingerprints difficult to employ on a smartphone [84]. Removing or modifying APs makes it challenging to use Wi-Fi technologies in indoor localization [107]. It is indeed challenging to produce an accurate, practical, low-cost, and real-time location system using wireless signals [25].

5.2.2. Challenges Related to Signal Strength

The four aspects related to challenges in signal strength are location and environment, coverage, stability, and noise. These aspects are explained in the following subsections.

a. Location and Environment

Most studies have concentrated on location as one of the issues. The inability to accurately and efficiently localize users in indoor environments for various purposes is still unsolved [13,80]. Indoor signals are affected by reflections, shadowing, multipath effects, high signal attenuation, and noise interference [61,72,77,118,120]. Hence, modeling radio propagation in an indoor context is definitely challenging [66,104]. The GNSS cannot work well in an indoor environment [28,69,72], as it is impossible to guarantee the availability of navigational satellite signals [3,99], it cannot provide a reliable indoor navigation solution [79,82,106], and it is incapable of tracking indoors [83]. The performance of GPS is limited due to its inability to penetrate solid building materials [64], reflection [8], signal attenuation [9,10], or weak reception of satellite signals [11–13]. Signal fluctuation may result in major localization errors [4]. The Wi-Fi fingerprint-based techniques are capable of excellent localization accuracy, but they cannot offer users semantic information about the object of interest [90]. Another issue with Wi-Fi is installing the APs and their locations [2,62]. Despite mobile devices staying stationary in some areas, gaining perfect positions is difficult [59]. In a complex indoor setting, reflection, diffraction, and scattering can be increased due to barriers in the form of walls, floors, furniture, and people [88]. Although RSSI in RFID is commonly used to locate active tags [19], its values shift often due to environmental factors despite the same device capturing data at the same position [81]. Another location challenge is the unknown initial position of the target [64] and the environmental impact on signal propagation that makes location determination susceptible to noise and crowding [107]. Traditional PDR is incapable of reliably locating the target in varied motion conditions [26].The PDR becomes less efficient in intricate interior areas, thus resulting in post-tracking failure to infer one's actual location in enclosed areas [94] and indoor corner recognition in crowd-sourced movement trajectories [11].

b. Coverage

In indoor localization, the network coverage should be sufficient to enable effective communication modes and minimize signal interference. The RSS-based individual localization is unreliable due to the low coverage of the anchor beacons [20]. The number and position of reference points on a mobile device tend to change with every update. This makes the modeling of the relationship between reference points and other locations in the radio map more complex [59]. Thus, coverage becomes limited based on signal interference [19,71]. The RSS suffers from signal availability, propagation effects, variability, and noise [107]. Despite employing an acoustic signal to achieve ranging-based localization, it has several drawbacks, such as a short operation distance [119].

c. Stability

Radio signals suffer from shadowing and multipathing in crowded areas, such as shopping malls, train stations, and airports [86,115], due to the presence of people and obstacles [110]. Wireless signal propagation can affect indoor localization [124]. However, it is vulnerable to interference, and its instability [65,123] can lead to attenuation in signal strength [67]. The RSSI is unstable due to indoor noise, interference, and obstructions that result in Wi-Fi localization errors [21] and poor location reliability [4]. Indoor localization that uses BLE beacons has substantial inaccuracies due to the instability of the BLE signal [96]. Conventional fingerprint localization is limited due to fingerprint ambiguity [106].

d. Noise

Unknown alterations to a signal that may occur during storage, transfer, or processing are collectively known as noise. The existing techniques have been experimentally adjusted for the measurement process and noise parameters, where the wrong settings can result in poor performance [70]. The PDR frequently differs from the truth due to the presence of noise in the sensing data [127]. PDR methods either have position drifts because of errors that add up over time or are delicate for different users [130]. Multipath effects and noise in the indoor environment can readily interfere with the RSS signal [76,124]. Noise also affects Wi-Fi output positions and Bluetooth output distances, particularly when users are on the move [86].

5.2.3. Challenges Related to Cost

The two aspects related to the challenges of cost are infrastructure and time consumption. These aspects are elaborated on in the following subsections:

a. Infrastructure

Indoor localization has several challenges, including costly infrastructure, time-consuming fingerprint gathering, and vulnerability to changing impediments [102]. Infrastructure refers to the APs of Wi-Fi and Bluetooth and knowledge of map constraints, which are required for localization. Additional infrastructure and self-designed equipment are required to ensure tracking precision by emitting and receiving ultrasonic signals. Due to high engineering complexity as well as high infrastructure and labor costs [12], the existing infrastructure-based indoor localization systems suffer from expensive installation, centralization, and poor reliability [134]. Due to changes in the local environment, the fingerprint database needs to be updated regularly [99,110] to remove ambiguities [99].

b. Time consumption

Time consumption affects the application of internal localization, mainly because some applications need to identify the target places, which incurs additional cost and takes time. For instance, AP installation depends on an automated system to discover the optimal sites for the AP, thus eliminating the need to apply conventional methods to determine optimal placements [62]. In addition, providing AP locations, propagation parameters (PPs), and radio maps would require the prior acquisition of Wi-Fi positioning systems, which can be very time-consuming and labor-intensive [79]. Instead of depending on crowded regions to decide on the ideal spots for installing them, Wi-Fi access points (WAP) are deployed geographically, which requires more human resources and higher costs [62]. However, the increasing density of fingerprints affects real-time performance, as additional time is required for fingerprint matching and probability distribution positioning [84]. Another problem is the time-consuming task of developing and maintaining a fingerprint database [73].

5.2.4. Challenges Related to Smartphone Position

There are many issues related to the position of the smartphone. The accelerometer and gyroscope data may differ if the user holds the smartphone casually or places it in a pocket or backpack, thus generating incorrect walking distance and direction estimates [3]. The system should handle transitions of smartphones from one position on the body to another by estimating the misalignment angle (MA) between the device orientation and the user direction [74]. Magnetometers in smartphones can measure geomagnetic field intensity (GFI), or the strength of the Earth's magnetic field. However, it is difficult to use GFI directly because the 3D readings of the magnetometer are in the phone's coordinate system and the change depends on how the phone is held [76]. When a smartphone changes its orientation, different vectors are obtained, and the magnetometer data are linked to the smartphone orientation [113]. In addition, the heading drift issue is still an obstacle for indoor pedestrian positioning [92].

5.2.5. Other Challenges

This section outlines the remaining issues that do not fall into any of the previous categories. It is difficult to determine the exact direction of a smartphone [118]. Localization accuracy can be increased by factoring in the user's movement information when detecting motion for different walking profiles [108]. Although using an acoustic signal for range localization has some drawbacks (e.g., short range, low update rate, and noise pollution), it is still a viable option [119]. Most of the existing particle filter-based technologies are either strongly influenced by motion estimate mistakes that result in an unstable system or are error-prone [113]. Step detection and SLE applied to various walking patterns are also some of the noted challenges [15].

5.3. Recommendations

This section summarizes the recommendations outlined in prior studies for further research directions. The suggestions are illustrated in Figure 7 based on usefulness classification.

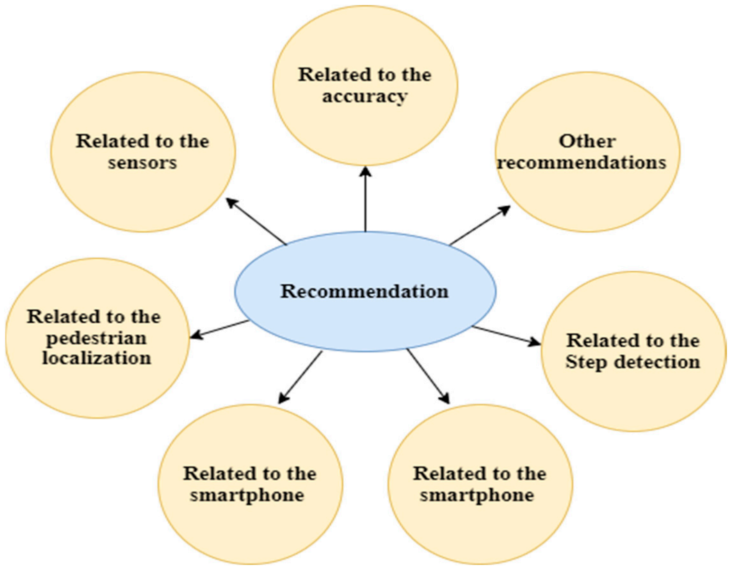

Figure 7. Overview of recommendations.

5.3.1. Recommendations Related to Accuracy

Some researchers recommended overcoming limitations related to accuracy by extending the current 2D tracking to 3D tracking in indoor localization [29,95]. The positioning accuracy can improve slightly as the number of beacons increases [107], besides determining the initial position with the least possible reference points [100]. In addition, recognizing the precise entrance position of the building and floor recognition can help build an indoor localization system [23].

To improve the accuracy of indoor localization, researchers have suggested investigating more complex landmark identification algorithms and applying semi-supervised and/or unsupervised learning approaches [11,77,81]. Others have concentrated on intrinsic restrictions, such as fixed output classes and extra datasets [100]. Some researchers suggested training multiple NNs (CNNs) [4,127], another fingerprinting approach using phones for positioning that consists of confidence-interval fuzzy models with fingerprinting of BLE signals and is based on NNs in the area of 85 m^2 to get the position 30 times faster when compared with trilateration [136]. Other studies have recommended integrating other indoor localization technologies, such as Wi-Fi, RFID, and Bluetooth, to improve localization accuracy [101]. Additional localization using coarse-grained Wi-Fi fingerprints could help score and validate alternative paths [125]. The threshold-based activity recognition cannot distinguish between different types of elevation, such as elevators, escalators, and stairs, especially in buildings where elevators pass across multiple floors [67].

5.3.2. Recommendations Related to Sensors

The recommendations presented in this subsection focus on sensors to enhance performance. A study suggested developing a ubiquitous integration platform to fuse wireless signals with MEMS sensor data to mitigate the effects of reflection, fading, and shadowing of wireless signals, apart from achieving a more reliable locating solution for smartphones and IoT devices [25]. Another study recommended incorporating other sources of information, such as the IMU on a smartphone or Bluetooth, to determine the motion of the smartphone [14]. There is a need to use more BLE sensors to gain excellent signal coverage across multiple rooms and lower measurement noise [18]. Using special techniques to optimize sensor placement, a researcher determined the best locations for each beacon [105]. However, RSS errors were not considered due to the shadow effect of body coverage. It would be desirable to consider new techniques to improve the data accuracy of IMU sensors to improve PDR localization accuracy [105,106]. On the other hand, the upper and lower floors have many common features, which can lead to misidentification. This problem can be solved by including additional sensors, such as a barometer [99].

5.3.3. Recommendations Related to Pedestrian Localization

Some researchers recommended adding multiple pedestrian localizations [71,124]. In addition, there is a need to invite more volunteers to participate in experiments [15]. The number of volunteers was limited in the study due to hardware issues encountered while using the RFID technology [20].

5.3.4. Recommendations Related to Technical Aspects

In order to improve indoor localization, researchers have suggested investigating more complex landmark identification algorithms and applying semi-supervised and/or unsupervised learning approaches [11,77,81]. Some studies focused on intrinsic restrictions, thus recommending fixed output classes and extra datasets for better implementation [100]. By using the deep learning method, Mag2D and Wi-Fi can be combined [76], while CNN must be trained [4,127]. Others proposed integrating other indoor localization technologies, such as Wi-Fi, RFID, and Bluetooth, to improve localization accuracy [101]. Additional localization using coarse-grained Wi-Fi fingerprints could help score and validate alternative paths [125].

5.3.5. Recommendations Related to Smartphone

A mobile phone can be carried in various ways, such as on the body, belt, pocket, hand, or bag, which should be explored to avoid restricting how a smartphone should be held by pedestrians [8]. There is a need to acquire heading estimation independent of various phone poses (phone in pocket or users swinging phones while moving) and motion state [94]. The unlimited location of a smartphone can pose serious problems for heading estimation in PDR systems [83]. Hence, it is vital to expand the range of applications as well as offer new walking patterns and phone positions [15]. The impact of changes in a user's actions (e.g., phone listening and phone in a pocket) should be taken into account [115] while concurrently considering different smartphone orientations [1]. More smartphone sensors should be integrated to improve the efficacy of the indoor localization system as well as the classification of locomotion activity [99]. More advancements can be initiated to extend the 2D tracking applications to 3D applications by employing smartphone barometers [97]. Variable phone models have differing inertial sensor performance characteristics, which might create localization errors due to sensor value gaps [23]. Furthermore, several drawbacks must be addressed, such as device heterogeneity and its effect on location identification accuracy [134].

5.3.6. Recommendations Related to Step Detection

A study proposed to develop a mechanism based on step detection to determine if the patient is moving excessively fast or in a strange way (e.g., in lockstep or lame), which could be a vital step in detecting errors in the patient's walking [18]. Further studies are needed to evaluate the mechanism for improving recognition accuracy, the relationship between anchor node position and system performance, and the effects of step length [64]. The introduction of step resizing and trajectory shape matching to known pathways is imminent as well [125]. More studies are sought to look into the transition step when walking, especially in a situation where Wi-Fi gives bad readings because it affects the estimation results [67]. Moreover, the angle of smartphones compatible with walking direction and complex pedestrian movements is largely unexplored [72].

5.3.7. Other Recommendations

This last category emphasizes the remaining recommendations from earlier studies that do not fit into the recommendation categories listed above. Recommendations for developing a mechanism that performs both range and direction determination simultaneously without the need to shake the phone can be found in several studies [118]. Developing a test using a large-scale dataset (more time, more varied walking patterns, and phone placements), as well as enhancing data collection accuracy, was prescribed in [100]. More studies should look into more complicated situations, such as pedestrian movements in zigzag patterns [27]. In addition, more semantic contexts for the grid model that restrict user movement and improve location estimation are sought [94]. Due to several experimental setbacks, localization studies were not carried out in a wide range of indoor locations [106]. Some researchers recommended slashing the cost of training and maintenance while boosting the reliability of the system [66].

5.4. Future Direction

This section provides general recommendations for future researchers interested in walking patterns and recognition systems. The following lists some significant points addressed for future development.

1. To collect data in real-time experiments on walking patterns, a researcher should choose the device based on the data that they wish to collect. Past studies deployed different devices to collect data. However, when using different smartphones, there is a problem of heterogeneity between the different platforms of the smartphones. Studies that intend to collect data related to walking patterns should use applications within a smartphone that include multiple sensors (gyroscopes, accelerometers, magnetometers, and barometers), which are necessary to detect walking patterns. A smartphone is preferred because it is equipped with multiple sensors that enable the detection of walking patterns and behavior.
2. Previous researchers used two types of participants (men and women), but the authors recommended studying different types of participants, such as men, women, children, limpers, and different walking patterns such as walking, fast walking, escalators, and elevators.
3. The literature mostly depicted the use of a small sample size (1–5 participants). However, it is important to gather a sample of 75 or more participants to ensure that the collected data are not "sample size dependent," thus resulting in accurate, valid, and generalizable results.
4. When a pedestrian walks in different patterns, the step length is affected. Other factors, such as height, gender, walking speed, and walking patterns, can influence step length. Therefore, there is a need to develop a better model based on the varied walking patterns and the details of participants mentioned above to generate a large dataset.
5. Most of the past studies evaluated different types of walking patterns. Some deployed the ML method to distinguish the various walking patterns. However, misunderstandings could happen when attempting to recognize the nature of walking patterns. One challenge in distinguishing walking patterns is feature extraction. For a recognition system to work efficiently with large datasets, deep learning algorithms are preferred

to recognize walking patterns. As such, CNN, RNN, and LSTM are proposed for the recognition system.

6. Conclusions

In this study, the SLR protocol was used to identify a wide range of aspects related to indoor localization. Referring to the SLR, indoor localization has been applied to numerous applications. Four databases were combed through to collect articles that examined indoor localization. In total, 109 articles were reviewed from the 4186 identified based on inclusion and exclusion criteria. This study unveils the technologies and methods deployed to develop indoor localization systems. While discussing the motivations, challenges, and recommendations linked to indoor localization using smartphones, several gaps were identified. In addition, the movement of pedestrians and phone poses are elaborated on in this paper. A critical analysis of the selected articles was undertaken to bridge some gaps detected in the literature. Furthermore, potential research directions are prescribed in this study, including developing a better model that embeds different walking patterns with various types of participants as well as incorporating CNN, RNN, and LSTM to recognize the walking patterns. Despite that, we reviewed several articles in our study that were selected based on inclusion and exclusion criteria that focused on smartphones, although researchers may combine smartphones with any other mobile device (such as tablets). The authors concentrated on various aspects of SLR. Moreover, researchers can undertake a quality assessment of each article based on its quality, content, and publishing source. In addition, there are overlaps in the classification of articles. Essentially, this study reveals several issues related to the topic area in preparation for future research endeavors.

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