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Systematic Review

Indoor Positioning Technologies: A PRISMA 2020 Cross-Technology Systematic Review of Accuracy and Deployment Requirements

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Abstract

Indoor positioning based on mobile-device sensors can support user guidance, location-aware services, and the occupancy-aware operation of smart buildings. However, selecting a positioning technology requires considering accuracy, implementation requirements, and validation conditions. We applied a five-criterion scoring framework to 222 Scopus-indexed studies published in 2020–2025 and selected through a Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020-guided systematic review. Six technology classes were assessed: Bluetooth Low Energy, ultra-wideband (UWB), WiFi, visible-light/vision-based positioning (VLP/VPS), pedestrian dead reckoning/inertial navigation (PDR/INS), and geomagnetic positioning. Ordinal scores from 1 to 5 (lower is more favorable) covered positioning accuracy, infrastructure density, setup and maintenance complexity, receiver device type, and validation realism. The technology classes differed significantly in total score and each criterion. Geomagnetic and PDR/INS systems had the lowest median total scores (2.60 and 2.80, respectively), mainly because they required no dedicated infrastructure, whereas VLP/VPS and UWB achieved better accuracy scores but generally required denser infrastructure. The accuracy score was inversely associated with a deployment burden score combining infrastructure density, setup complexity, and receiver device type. These findings can inform the selection of indoor positioning technologies for mobile navigation and potential occupancy-aware building applications; building energy use was not evaluated.

Keywords: indoor positioning systems; systematic review; cross-technology comparison; deployment burden; technology assessment; smart buildings

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1. Introduction

Indoor positioning systems (IPSs) are one of the fastest-growing research areas in navigation and localization. Demand for precise indoor localization comes from sectors including healthcare [1], warehouse logistics [2], construction [3], critical infrastructure management [4], and location-based services for individual users [5,6]. Unlike outdoor environments, indoor spaces lack direct access to satellite signals and have complex

geometry and variable signal propagation conditions, which require different technological approaches [7,8].

Indoor location information has also been investigated as an input for occupancy-aware building operation. An IPS-based system has been used to estimate the spatial distribution of occupants for demand-driven heating, ventilation, and air conditioning (HVAC) control [9], while WiFi probe signals have supported occupant-based lighting control in multi-person offices [10]. These applications show why the practical requirements of positioning systems matter beyond navigation alone.

Contemporary IPS solutions include radio, vision-based, inertial, and geomagnetic systems [2,11,12]. For the comparative analysis, however, a finer classification into six technology classes was adopted: Bluetooth Low Energy (BLE), ultra-wideband (UWB), WiFi, visible-light/vision-based positioning (VLP/VPS), pedestrian dead reckoning/inertial navigation systems (PDR/INS), and geomagnetic systems. These classes differ not only in their operating principles but also in infrastructure requirements, deployment complexity, and achievable accuracy, and each has a distinct deployment profile: radio systems require transmitter and receiver infrastructure or rely on existing infrastructure [13,14], vision-based solutions depend on lighting conditions and computational resources [15], inertial methods operate without additional infrastructure but are subject to the accumulation of drift error [16], and geomagnetic approaches exploit natural magnetic-field anomalies and therefore require extensive fingerprinting campaigns [17,18].

Systematic reviews and meta-analyses point to numerous IPS evaluation criteria, such as cost, scalability, energy consumption of positioning systems, positioning latency, reliability, and infrastructure complexity [8,19,20]. However, these criteria are defined and reported inconsistently, often only qualitatively and without common thresholds or reference scales [21,22]; in addition, individual studies rely on different datasets [23,24]. For this reason, some reviews still base comparisons primarily on positioning accuracy [7,21]. Such comparisons may not fully represent the practical requirements of deployment.

Despite the growing number of proposed evaluation frameworks [4,25,26], quantitative cross-technology methods for assessing the deployability of IPS remain limited [27,28]. ISO/IEC 18305 [29], the international standard for testing the performance of indoor localization systems, is cited in the literature [23], but its implementation remains inconsistent and is concentrated mainly in competition settings, such as the Indoor Positioning and Indoor Navigation (IPIN) competitions based on the EvAAL (Evaluating AAL Systems through Competitive Benchmarking) framework, and selected research consortia [25,30,31]. Technology-specific benchmarks also tend to focus on individual application domains, which limits comparison between technology classes [1,32]. The limited availability of standardized datasets and uniformly reported metrics may further reduce the comparability and reproducibility of results [19,23]. A common quantitative scheme for comparing positioning performance and deployment requirements across technologies is therefore still lacking.

This study develops and applies a common evaluation framework to a systematic review of six IPS technology classes. Applicability is represented by five dimensions: positioning accuracy, infrastructure density, setup and maintenance complexity, receiver device type, and realism of the validation conditions; deployment burden is represented by infrastructure density, setup and maintenance complexity, and receiver device type.

Mobile navigation and occupancy-aware building services are considered here as potential application contexts for the evaluated IPS technologies. The systematic review includes both infrastructure-dependent and infrastructure-free solutions. It does not evaluate a complete navigation system or building energy performance.

The analytical corpus comprised 222 publications from 2020 to 2025, selected through a process reported in accordance with the Preferred Reporting Items for Systematic

Reviews and Meta-Analyses (PRISMA) 2020, from an initial pool of 4323 records identified in Scopus. The period was chosen to cover recent IPS developments associated with new radio standards [33,34] and deep learning-based methods [13], while including only publications that had completed peer review by the search cutoff.

This study addresses the following research questions:

RQ1: What is the overall applicability profile of contemporary IPS in a cross-technology comparison, as measured by the five-criterion applicability score?

RQ2: Which scoring dimensions most strongly differentiate the individual technology classes?

RQ3: Is the positioning-accuracy score (S1) associated with the deployment-burden score (S2–S4)?

2. Materials and Methods

2.1. Scoring Framework

Two composite scores were defined: the total applicability score, calculated as the mean of S1–S5, and the deployment burden score, calculated as the mean of S2–S4. All criteria used an ordinal 1–5 scale, where 1 denoted the most favorable and 5 the least favorable result; for S1, lower scores therefore indicate higher positioning accuracy. S5 was not included in the deployment burden score because it describes the realism of the validation conditions, and thus the strength of the empirical evidence, rather than deployment effort. Missing criteria were handled by averaging the observed component scores; for example, a record with a missing S3 received a total score of (S1 + S2 + S4 + S5)/4. S1 was an inclusion requirement and at most two criteria could be missing, so each total score was based on at least three criteria; the deployment burden score required at least two of S2–S4 (219 records). Of the 222 records, 182 were complete, 35 lacked one criterion, and 5 lacked two (missing-data patterns in Supplementary Material S2). Composite scores were retained at full numerical precision for ranking and statistical tests. The derivation of both scores is shown in Figure 1.

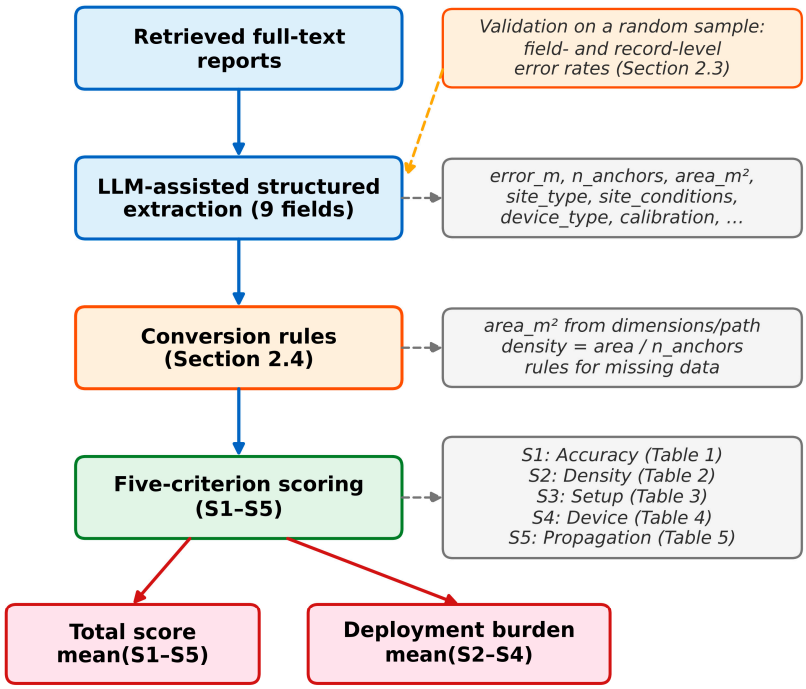


Figure 1. Overview of the extraction, conversion, and scoring pipeline used to derive the total applicability score (S1–S5) and the deployment burden score (S2–S4).

All criteria received equal weights in the baseline scenario because the literature does not support a universal hierarchy of these dimensions across IPS technology classes. The effect of this assumption was evaluated through the alternative-weighting and data-quality sensitivity analyses described in Section 2.5.

The selection of criteria stems from an analysis of the dimensions most frequently invoked in the review literature on IPS yet omitted from quantitative cross-technology comparisons [8,19,20,22,35]. In contrast to existing frameworks [19,21], the proposed scheme applies explicit scoring rules to each dimension, enabling comparisons across studies and technology classes. The numerical thresholds for S1 and S2 are operational definitions adopted for this comparison rather than generally accepted standards. The S1 thresholds separate centimeter-, decimeter-, sub-meter-, meter-, and room-level accuracy (Table 1). The S2 thresholds divide the area per device into equal 25 m^2 steps, where 25 m^2 corresponds to one device per 5 m × 5 m cell; in the corpus, the 25 m^2 and 75 m^2 thresholds lay close to the median (24.0 m^2) and upper quartile (79.6 m^2) of the area per device in infrastructure-based systems. S3–S5 are categorical scales defined by the operational descriptions given for Criteria 3–5 below. The sensitivity of the results to the numerical S1 and S2 thresholds was tested by changing them by ±20% (SA7, Section 2.5). The definitions of the individual criteria are presented below.

Criterion 1: 2D positioning accuracy. The mean positioning error in the horizontal plane, assessed against absolute thresholds (Table 1). The mean error (ME) was the preferred metric for all technology classes; if it was not reported, the median error or, for VLP/VPS only, the root mean square error (RMSE) [36,37] was extracted (sensitivity analysis SA4, Section 2.5). When no 2D value was reported, the 3D error was used (15 records), which is conservative because it is not smaller than its horizontal component. Accuracy was included in the total applicability score because a system with a very low deployment burden but insufficient accuracy may be of limited practical value.

Table 1. 2D Positioning Accuracy Assessment, informed by [38].

Score	Accuracy
1	< 0.10 m
2	0.10 to < 0.50 m
3	0.50 to < 1.00 m
4	1.00 to < 2.50 m
5	≥ 2.50 m

Criterion 2: Infrastructure density. The density of localization infrastructure in the test environment, expressed as the number of square meters per infrastructure device (Table 2). A higher value (more m^2 per device) denotes sparser infrastructure and a more favorable deployment score. A score of 1 was assigned only when the source explicitly indicated that no localization infrastructure devices were required. If the presence or number of such devices could not be established from the publication, S2 was treated as missing. The density value was calculated from the number of infrastructure devices reported in the publication and the test-area size determined according to the conversion rules described in Section 2.4.

Table 2. Infrastructure Density Assessment, with criteria informed by [39,40].

Score	Interpretation (m^2 per device)
1	No infrastructure devices (0)
2	≥ 75 m^2 per device
3	50 to < 75 m^2 per device
4	25 to < 50 m^2 per device
5	< 25 m^2 per device

Criterion 3: Setup and maintenance complexity. The amount of preparatory work required before system start-up, including calibration, fingerprinting, offline mapping, construction of radio databases, and periodic recalibration. The score reflects the workload and time needed to prepare the system for operation (Table 3).

Table 3. Initial Setup and Maintenance Complexity Assessment, with criteria informed by [35,41,42].

Score	Level	Operational definition
1	Minimal	Plug-and-play setup: no requirement for a radio map, fingerprint database, or prior surveying of anchor coordinates.
2	Low	Device-level calibration only: internal/external calibration, initial alignment, or limited base-station/anchor calibration without building a fingerprint database for the whole facility.
3	Moderate	Limited calibration or lightweight data collection: parameter tuning and/or partial or implicit data collection (e.g., online, crowdsourcing) without a dedicated measurement campaign covering the entire facility.
4	High	Full facility measurement campaign and/or extensive infrastructure calibration: fingerprint database, radio map, dense anchor deployment with measurements, simultaneous localization and mapping (SLAM), or in-situ training data collection.
5	Very high	Complex calibration; multi-sensor spatiotemporal calibration and/or periodic recalibration driven by environmental dynamics.

Criterion 4: Receiver device type. The type of device required by the end user or mobile platform reflects the entry barrier associated with hardware availability and cost (Table 4).

Table 4. Receiver Device Type Assessment, with criteria informed by [43–45].

Score	Device class	Operational interpretation
1	Consumer smartphone (app)	No additional hardware; minimal deployment burden.
2	Dedicated tag/transceiver or multi-smartphone configuration	Simple dedicated device or commodity-class phone; low integration burden.
3	Smartphone with external accessory or unspecified dedicated device	Additional hardware requirements or unclear form factor; moderate burden.
4	Dedicated wearable device (body- or head-mounted)	Requires mounting on the body and imposes alignment/attachment constraints.
5	Multi-sensor system mounted on a robot, unmanned aerial vehicle (UAV), or vehicle	Dedicated platform with multi-sensor payload, onboard computing integration, and power supply.

Criterion 5: Realism of validation conditions (test-environment propagation conditions). This criterion describes the extent to which the test environment corresponds to real deployment conditions, particularly with respect to line-of-sight and non-line-of-sight (LOS/NLOS) conditions, occlusion, multipath, and interference (Table 5). It does not directly measure deployment cost but rather the strength of the empirical evidence supporting the system's real-world applicability beyond laboratory conditions. A lower score denotes validation under more realistic conditions.

Table 5. Test Environment Propagation Conditions Assessment, with criteria informed by [46–48].

Score	Conditions	Operational interpretation
1	Severe NLOS/difficult propagation conditions	Heavily built-up, industrial, or underground environment; severe multipath effects, occlusion, and interference.
2	Predominantly NLOS	Frequent occlusion, limited direct line of sight, strong multipath effects.
3	Mixed LOS/NLOS	Typical indoor environment: corners, obstacles, intermittent blockage, mixed propagation.
4	Predominantly LOS	Mostly direct line of sight with only minor local obstacles/reflections.
5	LOS (clear line of sight)	Minimal occlusion, weak multipath; most favorable for signal propagation but least demanding as a validation scenario.

2.2. Search Strategy

Scopus was searched on January 24, 2026, using six separate queries designed for the individual technology classes: BLE, UWB, WiFi, geomagnetic systems, vision-based systems (VLP/VPS), and inertial/infrastructure-free systems (PDR/INS). The six classes were defined a priori by the leading technology and comprise systems that rely on infrastructure installed and managed at the building level or on sensors available in smartphones, which corresponds to the infrastructure and setup criteria of the framework (S2, S3). Systems led by cellular (LTE/5G) positioning, which typically depends on operator-managed network infrastructure, were therefore outside the scope, and RFID, infrared, and ultrasonic systems were not among the predefined classes; hybrid systems in which such a technology complemented one of the six classes were classified by their leading technology. The queries were based on the title, abstract, and keyword fields (TITLE-ABS-KEY) and combined technology-specific terms with terms related to indoor positioning, the type of solution (system/method/framework), and reported accuracy metrics, including mean error, mean absolute error, MAE, RMSE, and accuracy, with class-specific variants. The full wording of all search strategies is provided in Supplementary Material S1. Only a representative BLE query is included in the main text (Table 6).

Table 6. Example of a Scopus search query for BLE.

TITLE-ABS-KEY(("bluetooth low energy" OR "bluetooth low-energy" OR ble OR ibeacon OR "bluetooth beacon" OR "ble beacon") AND (indoor AND (positioning OR localization OR localisation OR navigation)) AND (system OR method OR framework) AND ("mean error" OR "mean absolute error" OR mae OR rmse OR accuracy)) AND PUBYEAR > 2019 AND PUBYEAR < 2026 AND (LIMIT-TO(SUBJAREA, "ENGI") OR LIMIT-TO(SUBJAREA, "COMP")) AND (LIMIT-TO(DOCTYPE, "ar") OR LIMIT-TO(DOCTYPE, "cp")) AND (LIMIT-TO(LANGUAGE, "English"))

All queries were limited to 2020–2025, the Engineering and Computer Science subject areas, articles and conference papers, and English-language records. Review publications, editorials, and works without primary research results were excluded from the scoring corpus. Open-access status was not an eligibility criterion. The searches returned 4323 records. Scopus was selected for its broad coverage of engineering and computer science literature and its reproducible search syntax.

The systematic review was reported with reference to PRISMA 2020; item-level reporting is documented in the accompanying checklist. The study was not registered, and no protocol was prepared.

2.3. Study Selection

Screening and full-text eligibility assessment were performed by two authors, with decisions reached by consensus; data extraction was performed by the same authors with the support of a language model (stage 5). The publication selection process is presented in the PRISMA flow diagram (Figure 2) and comprised the following stages, conducted in accordance with PRISMA 2020:

1. Deduplication. From the pool of 4323 records, 820 duplicates were removed in two sequential steps: first based on the digital object identifier (DOI) (785 removed), then based on the normalized title (35 removed). After deduplication, 3503 unique records remained. The deduplication script is provided in Supplementary Material S3.
2. Automated pre-screening. A deterministic Python (version 3.13) pipeline applied title- and abstract-based rules (Supplementary Material S4), excluding 2939 records and retaining 564 for title-and-abstract screening; references to simulation did not trigger automatic exclusion. The rationale for each rule and the number of records it flagged are given in Supplementary Material S10. Forty-seven records from a list of 78 studies identified during an earlier, narrative phase of the project were retained irrespective of the rules (rule R0); omitting the 26 included records retained only through R0 did not change the two leading rank positions ($\varrho = -0.411$ vs. -0.408 for S1 and the deployment burden score; Supplementary Material S6). A stratified random sample of 100 automatically excluded records, assessed by two authors by consensus from titles and abstracts, gave a false-exclusion rate of 20% (95% Clopper–Pearson confidence interval 12.7–29.2%), mainly due to the accuracy-metric rule (14 of 20 cases; Supplementary Materials S10 and S11; Section 4.4, Limitation 6).
3. Title-and-abstract screening. Of the 564 records screened, 59 were excluded and 505 were directed to full-text retrieval. These final decisions incorporated the re-examination of 92 records initially excluded on the basis of abstract-level accuracy-metric or technology/application-scope criteria.
4. Full-text retrieval. Of the 505 reports sought, 229 could not be obtained despite institutional access, interlibrary loans, and open sources. The remaining 276 reports proceeded to full-text eligibility assessment.
5. Data extraction from full texts was performed with the assistance of the OpenAI o1-pro language model using the structured prompt provided in Supplementary Material S5. The model supported extraction, whereas publication-inclusion decisions and ambiguous cases were resolved through manual full-text review.
6. Extraction validation was performed on a random sample of 60 records (39% of the first-round records), stratified proportionally by technology class and drawn from the records extracted in the first round. Extraction errors were assessed at the field and record levels. The error rate was 1.5% at the field level and 3.3% at the record level (2 of 60 records), with a record considered erroneous if it contained at least one error in any field.
7. Full-text screening. Of the 276 reports assessed for eligibility, 54 were excluded, each with one primary reason: lack of experimental validation (simulation only; $n = 5$), a leading technology outside the systematic review scope ($n = 1$), and lack of an error value in the selected metric ($n = 48$). Re-assessment under the clarified metric rule excluded one previously included UWB report that gave only RMSE and maximum error. Ultimately, 222 publications were included in the analytical corpus.

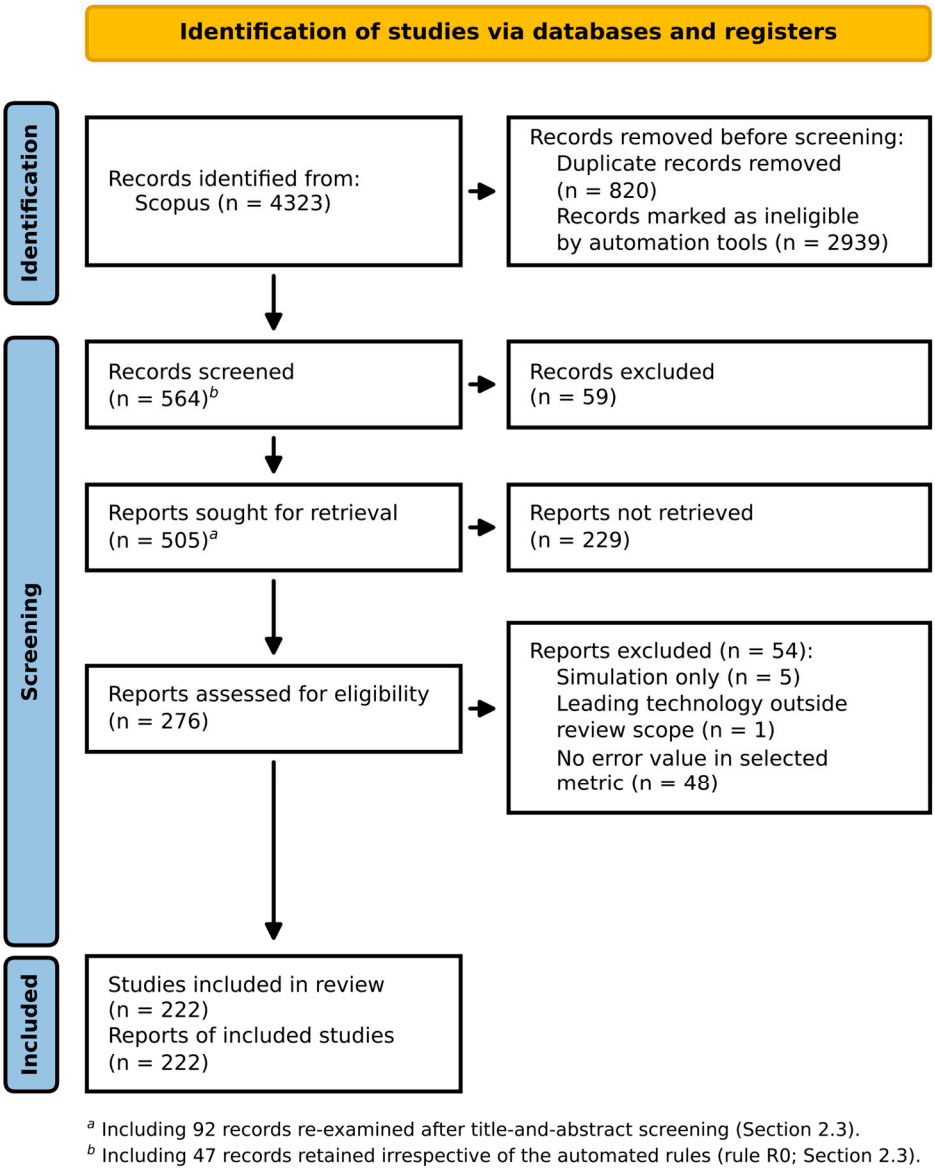


Figure 2. PRISMA 2020 flow diagram for selection of the scoring corpus.

2.4. Data Extraction and Conversion Rules

The analytical dataset is provided in Supplementary Material S2. For each publication, the bibliographic, technological, environmental, infrastructure, receiver, and accuracy data required to assign S1–S5 were extracted according to the rules in Supplementary Material S5. Estimated or unresolved inputs were flagged. The S4 codes of all records were checked for consistency with the extracted device descriptions and Table 4, and 14 records were recoded (marked in Supplementary Material S2). Publications were eligible if they reported an accuracy value, had an unambiguously defined leading technology, and lacked no more than two scoring inputs.

The test-area size was determined from the information reported in each publication. Explicitly stated areas were used directly, reported dimensions were converted to m^2, and the areas of multiple floors were summed when the source permitted reliable calculation. When only a test-path length was available, area was estimated as path length multiplied by an assumed corridor width of 3 m. When no quantitative geometry was reported, a predefined facility-description rule was applied: 50 m^2 for a single room, 200 m^2 for a

group of rooms, and 1000 m² for a full building. Estimated areas were flagged and used to calculate infrastructure density (S2).

Infrastructure-device counting included only devices serving as localization anchors, such as BLE beacons, UWB anchors, WiFi access points, and light-emitting diode (LED) luminaires. Servers, gateways, synchronization modules, and other auxiliary devices were excluded because they do not directly represent the spatial infrastructure footprint and do not scale proportionally with facility area.

Leading technology classification. Given the prevalence of fusion approaches combining multiple sensors and technologies, publications were classified according to the leading technology, understood as the dominant component responsible for producing the final position estimate. In publications reporting more than one configuration or several test scenarios, data were extracted from the variant validated on the largest reported area or in the most extensive test environment. In this way, variants more representative of deployment conditions were preferred over configurations achieving the lowest error under laboratory conditions.

A formal risk of bias assessment at the level of individual studies was not performed. This was due to the heterogeneous nature of the included experimental studies, encompassing different technologies, test environments, metrics, and validation schemes, for which no single standardized assessment tool adequate for the entire corpus was identified. To limit the impact of this heterogeneity, rigorous eligibility criteria, explicit data extraction and conversion rules, and a sensitivity analysis of the results were applied.

No formal synthesis-level assessment of reporting bias or certainty of evidence was performed.

2.5. Statistical Analysis

Statistical analysis was conducted separately for the total applicability score (S1–S5) and the deployment burden score (S2–S4). Because the proposed scoring scheme generates ordinal-scale data, the results are presented using medians. The Kruskal–Wallis test was used as a nonparametric omnibus test to compare the rank distributions of scores across the six independent technology classes [49,50]. The test assesses whether at least one class distribution differs from the others but does not identify the differing pairs. Each criterion-level test used the records with an observed value for that criterion. The H statistic, degrees of freedom, the number of records contributing to each test, the *p*-value, and the eta-squared effect size based on the H statistic, computed as $\eta^2_H = (H - k + 1)/(n - k)$ [51], were reported. In the case of a significant omnibus result, pairwise comparisons were performed using Dunn's test with Bonferroni correction [52,53]. Spearman's rank correlation was used to assess the relationship between positioning accuracy (S1) and the remaining scoring dimensions [54,55]. The correlation analysis used the deployment burden score defined as the mean of criteria S2–S4, because it captures deployment burden while avoiding the part-whole dependence resulting from the presence of S1 in the total applicability score. To separate the association within technology classes from differences between them, a class-adjusted partial Spearman correlation was calculated as the Pearson correlation between the residuals of the ranks of S1 and of the deployment burden score, each regressed on technology-class indicator variables. The reference t test used $n - k - 2$ degrees of freedom, with $k = 5$ technology-class indicators. Confidence intervals (95%) for the pooled and partial coefficients were obtained by the percentile bootstrap with 5000 resamples of records. The statistical significance level was set at $p < 0.05$.

The robustness of the technology-class ranking was assessed in seven sensitivity analyses (Supplementary Material S6): doubling the weight of each criterion in turn (SA1a–SA1e); excluding records with an estimated test area (SA2); restricting the analysis to complete records (SA3); converting RMSE and median values to mean-error

equivalents (Rayleigh and half-normal error models) and restricting S1 to explicitly reported mean errors (SA4); treating S2 as not assessable for infrastructure-based records validated on areas below 50 m² (SA5a) or 100 m² (SA5b); omitting each criterion in turn, and S2 and S4 together (SA6); and multiplying all S1 and S2 thresholds by 0.8 or 1.2, independently and jointly (SA7). In each scenario, the Kruskal–Wallis and Dunn tests for the total score were repeated to assess whether the between-class differences remained significant. Tied medians received the same (minimum) rank, and distribution-free 95% confidence intervals for the class medians were calculated from order statistics [50].

Potential retrieval bias was assessed by comparing retrieved and non-retrieved reports (n = 505) on characteristics available in Scopus for both groups: technology class, publication year, document type, publisher, screening pathway, and the smallest error value reported in the abstract (Pearson's chi-square test with Cramér's V and Monte Carlo p-values for sparse tables; Mann–Whitney U test; Supplementary Material S9).

3. Results

3.1. Characteristics of Included Publications

The analytical corpus included 222 system instances drawn from 222 publications. Classification by leading technology yielded the following distribution: WiFi (n = 86), UWB (n = 35), VLP/VPS (n = 32), BLE (n = 31), PDR/INS (n = 20), and geomagnetic systems (n = 18). Technology combinations accounted for 37% of the corpus and were classified by the dominant component. WiFi systems used access points as anchors and consumer smartphones as receivers in 57 of the 79 records with a coded receiver, and 16 of the 86 WiFi systems were combined with inertial sensing. UWB systems used dedicated anchors (median 4 per test area) and tags, and 14 of the 35 fused UWB ranging with inertial or odometric data. VLP/VPS systems were mainly based on LED luminaires (28 of 32 records involved VLP) and on photodiode or camera receivers, which were often custom-built or attached to a smartphone (S4 = 3 in 18 records). BLE systems used beacons or anchors (median 6.5 per test area) with smartphones (15 of 30 records with a coded receiver) or dedicated tags. PDR/INS systems estimated displacement from step detection, step length, and heading (PDR) or from integrated inertial measurements (INS), and in 14 of the 20 records the accumulated drift was corrected by fusion with geomagnetic, WiFi, BLE, UWB, or visual measurements. PDR/INS and geomagnetic systems used the inertial sensors and magnetometers of smartphones or wearable devices; 12 of the 20 PDR/INS and 13 of the 18 geomagnetic systems required no positioning infrastructure, and PDR was the most frequent complement of geomagnetic positioning (7 of 18). Bibliographic data, extracted characteristics, and scores of all included studies are provided in Supplementary Material S2.

Full texts were retrieved for 276 of the 505 records directed to retrieval (54.7%). Retrieval did not differ significantly by technology class ($\chi^2(7) = 6.09$; $p = 0.529$; Cramér's V = 0.110; eight categories, including records matching several classes or none) or screening pathway ($p = 0.703$), and the abstract-reported errors of retrieved and non-retrieved reports did not differ significantly (median 0.65 vs. 0.41 m; $p = 0.091$); within classes, only the geomagnetic comparison reached significance ($p = 0.042$; four non-retrieved values). Retrieval was higher for journal articles than for conference papers (67.6% vs. 31.5%), varied by publisher, and decreased for recent publications (from 89.6% in 2020 to 37.5% in 2025; $p < 0.001$ for each). Among the included records, the abstract-reported error was strongly correlated with the full-text error (Spearman's $\varrho = 0.934$; $n = 151$), which supports its use as a screening-level proxy (Supplementary Material S9).

3.2. Scoring Results by Technology Class

Table 7 presents the medians for the five component criteria and the total score, broken down by the six technology classes. The same medians are visualized as a heatmap in Figure 3.

Table 7. Median criterion and total applicability scores (1 = most favorable, 5 = least favorable).

Technology	*n*	S1 Accuracy	S2 Density	S3 Setup	S4 Device	S5 Propagation	Total
BLE	31	4.0	4.0	3.0	1.5	3.0	3.20
UWB	35	2.0	5.0	3.0	3.0	3.0	3.00
WiFi	86	4.0	4.0	4.0	1.0	3.0	3.00
VLP/VPS	32	1.0	5.0	3.5	3.0	5.0	3.20
Geomagnetic	18	3.0	1.0	4.0	1.0	3.0	2.60
PDR/INS	20	3.0	1.0	4.0	1.0	3.0	2.80

Geomagnetic systems had the lowest (most favorable) median total score (2.60), followed by PDR/INS (2.80) and by UWB and WiFi systems (3.00 each), while BLE and VLP/VPS reached the highest (least favorable) median of 3.20. These values are descriptive summaries within the adopted scoring framework. Despite similar total scores, the classes differed in their component profiles, indicating different combinations of accuracy and deployment requirements.

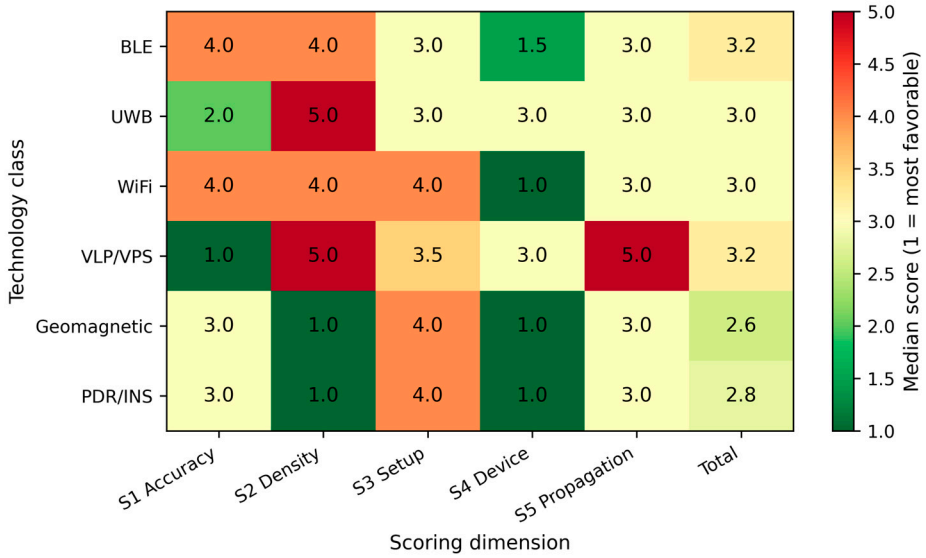


Figure 3. Heatmap of median scores by technology class (1 = most favorable, 5 = least favorable).

The heatmap of medians shows that VLP/VPS and UWB systems had the lowest accuracy scores, corresponding to higher reported positioning accuracy, but also the highest infrastructure-density scores. WiFi systems combined low end-user hardware requirements with higher setup complexity associated with the prevalence of fingerprinting. Geomagnetic and PDR/INS systems had lower infrastructure and hardware scores but higher accuracy scores than UWB and VLP/VPS. The distribution of total score values within the individual technology classes is presented in Figure 4.

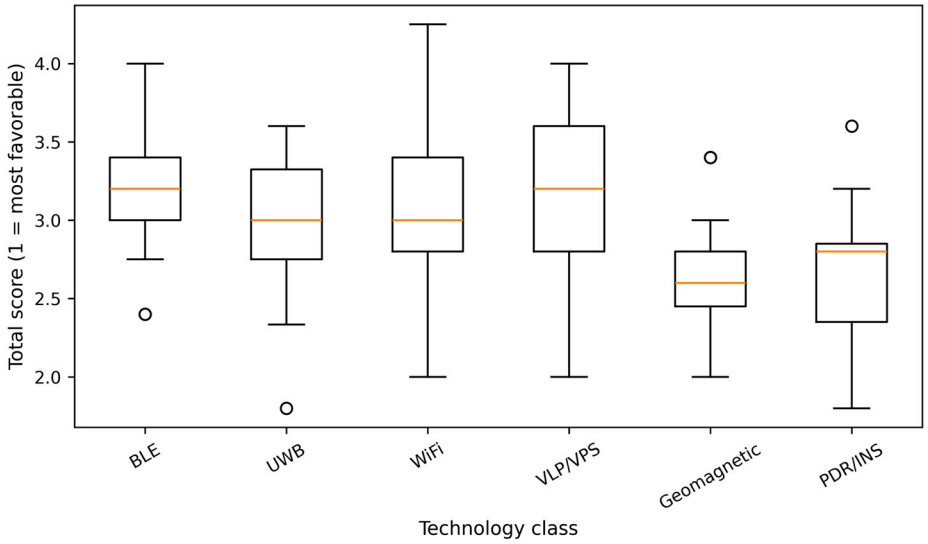


Figure 4. Total five-criterion score by technology class (lower scores are more favorable).

3.3. Comparison Between Technology Classes

The Kruskal–Wallis tests indicated differences between technology classes for the total score and all five component criteria (Figure 5). The largest effects were observed for positioning accuracy ($H(5) = 114.73$; $n = 222$; $p < 0.001$; $\eta^2_H = 0.508$) and infrastructure density ($H(5) = 78.61$; $n = 204$; $p < 0.001$; $\eta^2_H = 0.372$), followed by receiver device type ($H(5) = 52.76$; $n = 214$; $p < 0.001$; $\eta^2_H = 0.230$), setup complexity ($H(5) = 39.98$; $n = 216$; $p < 0.001$; $\eta^2_H = 0.167$), and propagation conditions ($H(5) = 27.70$; $n = 209$; $p < 0.001$; $\eta^2_H = 0.112$). The total score also differed between classes ($H(5) = 31.66$; $n = 222$; $p < 0.001$; $\eta^2_H = 0.123$).

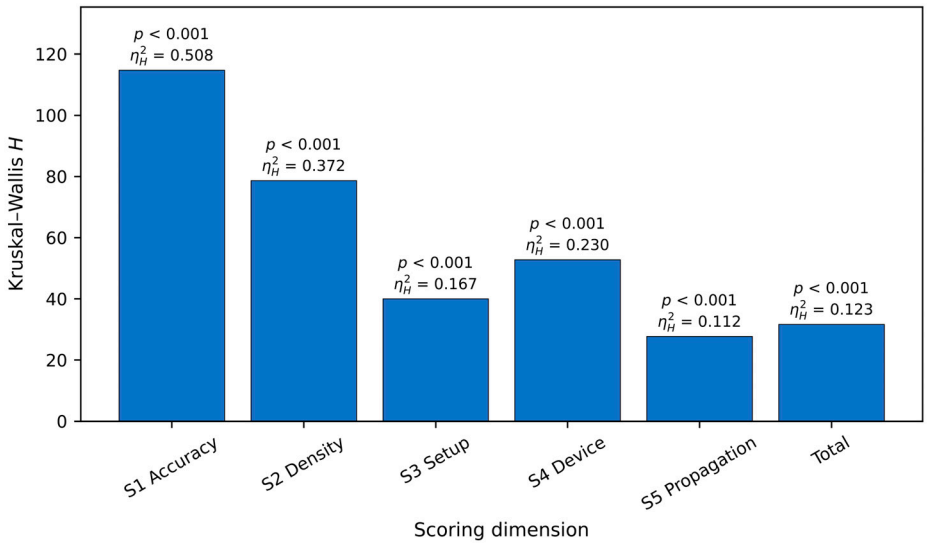


Figure 5. Kruskal–Wallis results by scoring dimension.

The results of Dunn's post hoc pairwise comparisons for the total score are presented in Figure 6a. Geomagnetic and PDR/INS systems had lower scores than BLE ($p = 0.002$ and $p = 0.005$, respectively), WiFi ($p = 0.001$ and $p = 0.003$), and VLP/VPS ($p = 0.002$ and $p = 0.005$). Geomagnetic systems also scored lower than UWB ($p = 0.036$), whereas the comparison of PDR/INS with UWB did not reach significance after Bonferroni correction ($p = 0.085$), and the geomagnetic and PDR/INS classes did not differ from each other. The non-significant comparisons should be interpreted in light of the smaller geomagnetic and

PDR/INS groups (n = 18 and n = 20). The BLE, UWB, WiFi, and VLP/VPS classes did not differ significantly from one another in the total score, although their descriptive component profiles differed. Complete numerical Dunn matrices are provided in Supplementary Material S7.

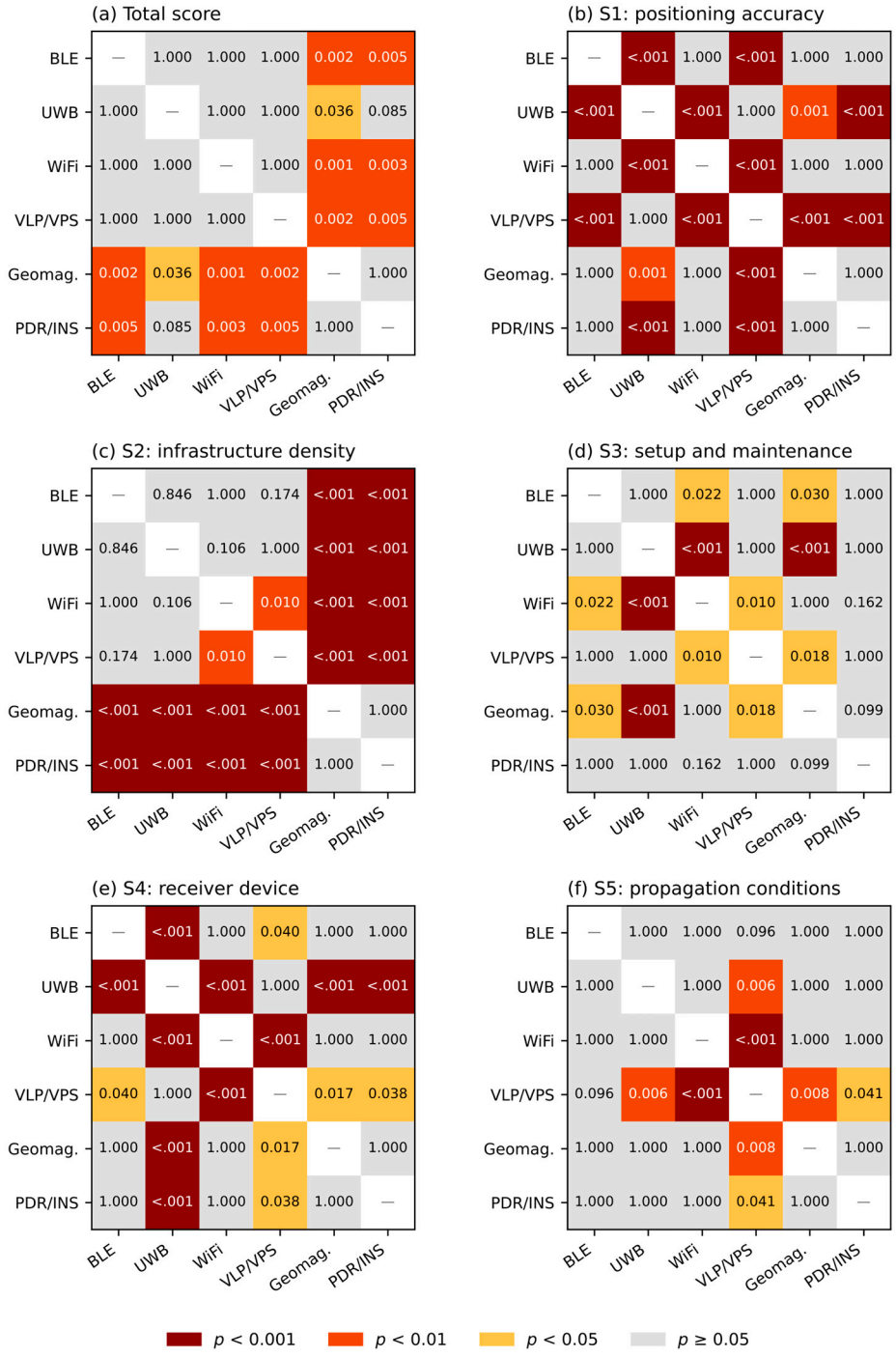


Figure 6. Dunn post hoc pairwise comparison matrices with Bonferroni-corrected p-values: (**a**) total score; (**b**) positioning accuracy (S1); (**c**) infrastructure density (S2); (**d**) setup and maintenance complexity (S3); (**e**) receiver device type (S4); (**f**) test-environment propagation conditions (S5).

Positioning accuracy (S1). This criterion showed the largest between-class differences. VLP/VPS systems had the lowest median S1 score (1.0)—26 of 32 studies reported an error below 0.10 m, including several studies with errors on the order of 0.01 m [56–58]. UWB systems had the next-lowest median S1 score (2.0), with the best results at or

below 0.05 m [59,60]. BLE had a median S1 of 4.0; most BLE systems reported errors in the range of 1.0–2.5 m, and three systems, including [61,62], reported an error below 0.50 m, all with dense beacon infrastructure (S2 = 5). Eight of the 15 pairwise comparisons were significant in the post hoc analysis, and their distribution is presented in Figure 6b. Significant contrasts included VLP/VPS versus BLE, WiFi, geomagnetic systems, and PDR/INS, and UWB versus BLE, WiFi, geomagnetic systems, and PDR/INS.

Infrastructure density (S2). This criterion showed the second-largest between-class differences. Most geomagnetic systems (median S2 = 1.0; 13 of 18 systems) and PDR/INS systems (median S2 = 1.0; 12 of 20 systems) were coded as infrastructure-free because they relied on built-in smartphone sensors (magnetometer or inertial measurement unit, IMU) or local indoor magnetic-field anomalies. VLP/VPS and UWB had median S2 scores of 5.0, corresponding to the densest infrastructure category. For VLP, this pattern reflects the limited range and directionality of optical transmission—for example, 4 LED luminaires per 25 m^2 [63] or 1 luminaire per 2 m^2 [56]. For UWB, dense anchor placement [64] supports precise ranging but increases deployment requirements. WiFi showed the widest spread (median 4.0; interquartile range, IQR, 2.0–5.0), reflecting differences between systems using a small number of dedicated commodity transceivers [65] and systems exploiting a dense set of pre-existing WiFi and cellular transmitters [66]. Nine of the 15 pairwise comparisons were significant, the largest number among the five criteria (Figure 6c). Geomagnetic and PDR/INS systems differed significantly from each infrastructure-dependent class, indicating a consistent separation in S2 within the reviewed corpus.

Setup and maintenance complexity (S3). This criterion showed the fourth-largest between-class differences. WiFi exhibited a high median complexity (S3 = 4.0), which stems from the prevalence of fingerprinting approaches requiring the construction of a radio database covering the entire test facility. In the WiFi class, 69 of 86 systems required a site-wide fingerprinting campaign (S3 = 4); systems with lower setup effort were exceptions [67]. Geomagnetic systems also require extensive fingerprinting (median S3 = 4.0), because position estimation relies on a magnetic anomaly map [68,69]. UWB and BLE showed the lowest median complexity among infrastructure-dependent systems (S3 = 3.0). Although anchor-coordinate measurement was common in many UWB systems, anchor-free relative approaches such as LUVI were also represented [70]. Six of the 15 comparisons were significant in the post hoc analysis (Figure 6d): BLE vs. WiFi, BLE vs. Geomagnetic, UWB vs. WiFi, UWB vs. Geomagnetic, WiFi vs. VLP/VPS, and VLP/VPS vs. Geomagnetic. This result indicates that BLE, UWB, and VLP/VPS had a lower setup burden than WiFi and geomagnetic systems, whereas they did not differ significantly from one another after Bonferroni correction.

Receiver device type (S4). WiFi (median S4 = 1.0; 57 of 86 systems used only a smartphone), PDR/INS (median S4 = 1.0; 15 of 20 systems used a smartphone), and geomagnetic systems (median S4 = 1.0; 14 of 18 systems used a smartphone) showed the lowest hardware barrier. This reflects the widespread availability of WiFi modules, IMUs, and magnetometers in standard consumer smartphones. UWB had a median S4 of 3.0 with a large spread (IQR 2.0–4.0). VLP/VPS (median S4 = 3.0) often requires a dedicated photodetector or camera; 9 of 32 studies used a standard smartphone as the receiver device. For S4, 8 of the 15 pairwise comparisons remained significant after Bonferroni correction, all of which involved UWB or VLP/VPS, and their distribution is presented in Figure 6e. This indicates that hardware barriers mainly separate classes relying on dedicated receivers from smartphone-based classes and differentiate the technology classes less strongly than accuracy or infrastructure density.

Propagation conditions (S5). This criterion showed the smallest, though still statistically significant, between-class effect. VLP/VPS systems were validated mainly under favorable LOS or predominantly LOS conditions (median S5 = 5.0), consistent with the

requirement for a direct line of sight to the light source. Typical test environments were small laboratory rooms [56,57]. PDR/INS showed a median S5 of 3.0 with an upper quartile of 4.0, which may partly reflect validation on unobstructed corridor trajectories. BLE and WiFi showed medians of 3.0, corresponding to typical mixed LOS/NLOS conditions. Lower S5 values were reported in BLE [71,72] and geomagnetic [73] systems evaluated in large, complex indoor environments. S5 produced the fewest significant pairwise differences, as shown in Figure 6f. After Bonferroni correction, all four significant comparisons involved VLP/VPS (versus UWB, WiFi, geomagnetic, and PDR/INS systems), suggesting that pairwise separation based on this criterion was driven mainly by the favorable validation conditions of VLP/VPS systems.

3.4. Correlation Between Accuracy and Deployment Burden

To address RQ3, the relationship between the positioning-accuracy score (S1; lower values indicate higher accuracy) and the deployment burden score, calculated as the mean of S2–S4, was analyzed. A graphical representation of this relationship is presented in Figure 7.

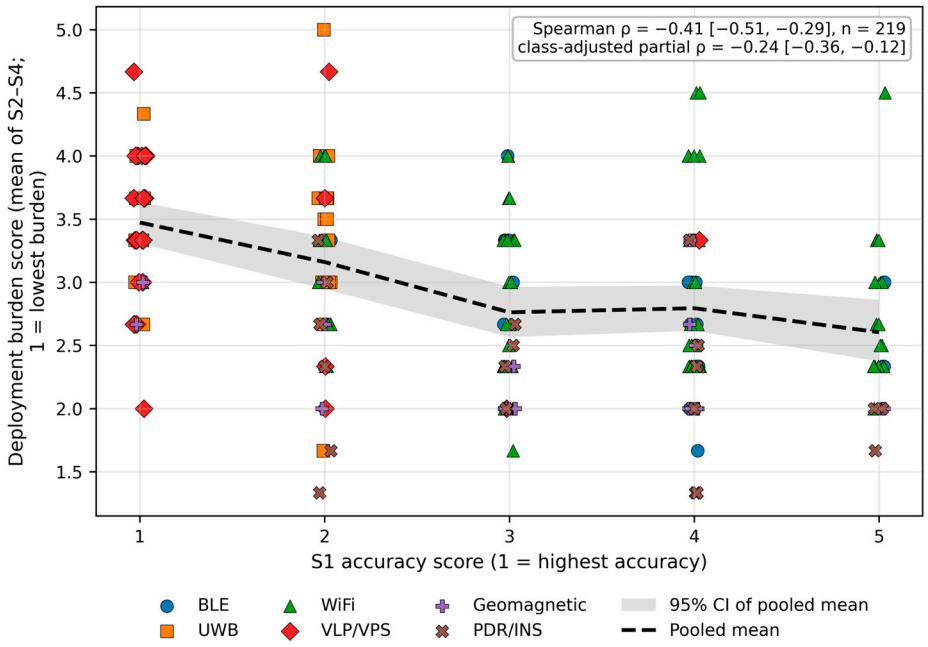


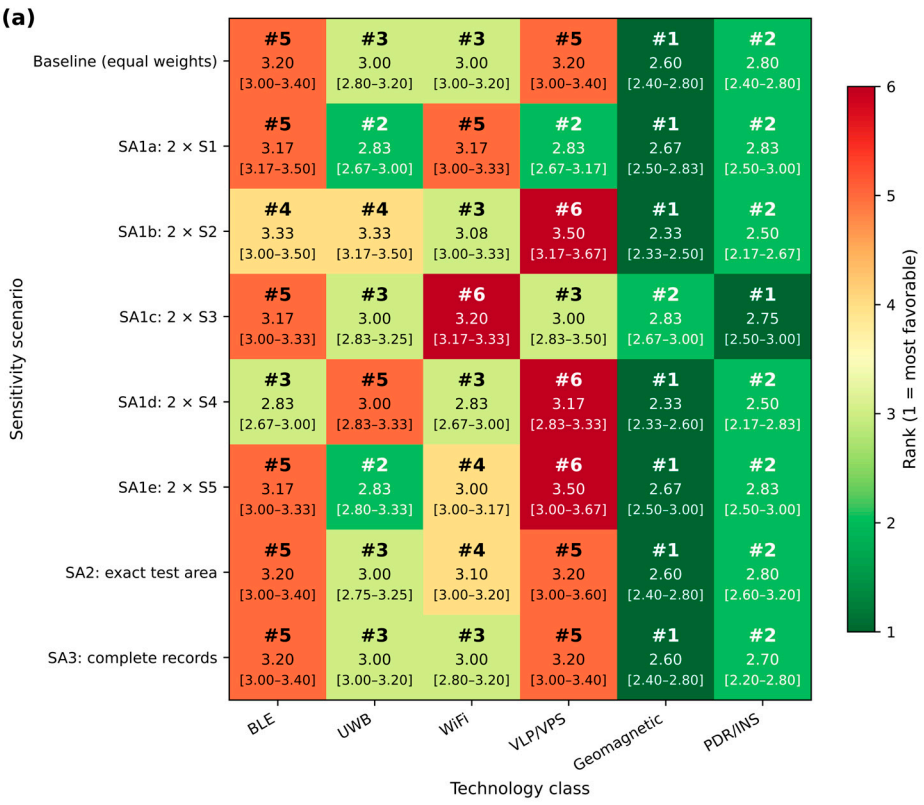
Figure 7. Positioning-accuracy score versus deployment burden (Spearman rank correlation). The dashed line shows the pooled mean deployment burden score at each S1 level and the shaded band its bootstrap 95% confidence interval; points are jittered horizontally.

VLP/VPS systems combined low S1 scores with higher infrastructure and hardware requirements, whereas geomagnetic and PDR/INS systems combined moderate S1 scores with lower deployment-burden scores. At the pooled-record level, a moderate negative association was observed (Spearman's ϱ = −0.408; 95% confidence interval (CI) [−0.515, −0.293]; $p < 0.001$; $n = 219$): lower S1 scores, corresponding to higher reported accuracy, tended to co-occur with higher deployment-burden scores. The association was weaker after adjustment for technology class (partial ϱ = −0.239; 95% CI [−0.361, −0.116]; $p < 0.001$) and reached significance within a class only for BLE (ϱ = −0.511; $p = 0.003$); it therefore reflects mainly differences between classes. The burden components were not associated with S1 in a uniform direction (all $p < 0.001$): the association was negative for infrastructure density (ϱ = −0.353) and receiver device type (ϱ = −0.537) but positive for setup and maintenance complexity (ϱ = 0.318), because site-wide fingerprinting was concentrated in the

classes with higher reported error. Propagation conditions (S5), which are not part of the burden score, were also negatively associated with S1 ($\varrho = -0.327$; $p < 0.001$), indicating that the most accurate results were more often obtained under favorable LOS conditions. The composite burden score therefore aggregates components with opposing relationships to accuracy, and the association is descriptive rather than causal.

3.5. Sensitivity Analysis

The rankings obtained in the sensitivity analyses are shown in Figure 8 (median total scores for all variants in Supplementary Material S6). Geomagnetic systems ranked first in every weighting and data-quality scenario (SA1–SA3) except SA1c, in which they ranked second behind PDR/INS; PDR/INS systems ranked first or second in all these scenarios, but shared second place with UWB and VLP/VPS when S1 was doubled (SA1a) and with UWB when S5 was doubled (SA1e). In SA4, metric conversion did not change the class medians, and the two leading positions were retained for records with an explicitly reported mean error ($n = 131$), although in this subset the S1 median of PDR/INS increased from 3 to 4 and the total median of BLE decreased from 3.20 to 3.00. Among infrastructure-based records, test-area size was strongly associated with the area per localization device ($\varrho = 0.749$; $p < 0.001$), and 28 of the 32 VLP/VPS and 15 of the 35 UWB systems were validated on areas smaller than 50 m²; in SA5, geomagnetic systems remained at rank 1, whereas VLP/VPS moved from rank 5 to rank 2 and PDR/INS from rank 2 to rank 3 (SA5a) or 4 (SA5b). In SA7, changing the S1 and S2 thresholds by ±20% kept geomagnetic systems at rank 1 and PDR/INS at rank 2 (shared rank 1 in one variant) in all eight variants, whereas the intermediate classes again changed positions.



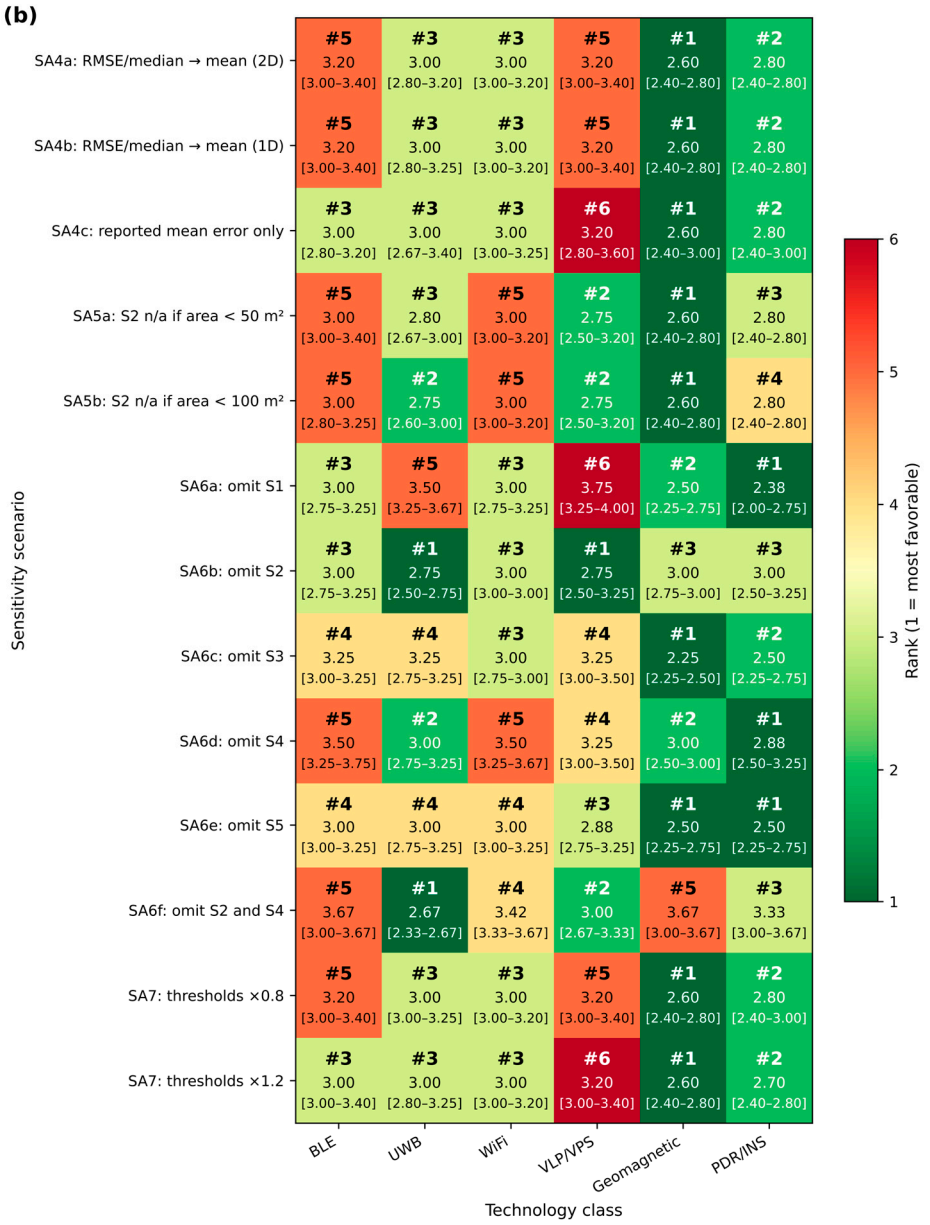


Figure 8. Ranking stability across sensitivity analyses: (**a**) baseline and SA1–SA3; (**b**) SA4–SA6 and the joint ±20% threshold perturbations of SA7 (all variants in Supplementary Material S6). Each cell shows the rank, the median total score, and its 95% confidence interval; classes with equal medians share the same rank.

In SA6, omitting S1, S3, S4, or S5 did not displace geomagnetic and PDR/INS systems from the two leading positions (after omitting S4, geomagnetic systems shared rank 2 with UWB), whereas omitting S2 moved UWB and VLP/VPS to rank 1 (median 2.75) and geomagnetic and PDR/INS systems to rank 3 (median 3.00, shared with BLE and WiFi); when S2 and S4 were both omitted, geomagnetic systems ranked fifth. The leading positions therefore depend on S2, that is, on the absence of dedicated positioning infrastructure. The intermediate classes were sensitive to the weighting (UWB ranked between 2 and 5, WiFi between 3 and 6, BLE between 3 and 5, and VLP/VPS between 2 and 6), and their ordering should be regarded as indicative.

In the baseline scenario, the 95% confidence intervals of the geomagnetic and PDR/INS medians did not overlap with those of BLE, WiFi, and VLP/VPS and met that of UWB only at its lower bound (2.80), whereas the intervals of the four intermediate classes overlapped (Figure 8), consistent with the Dunn test for the total score (Section 3.3). Rank

positions order the class medians and do not by themselves indicate significant differences. The weighting affects only the composite scores and the ranking, not the criterion-level medians, tests, or correlations. The Kruskal–Wallis test for the total score remained significant in every scenario ($p \leq 0.005$). All seven significant baseline Dunn contrasts were retained under metric conversion (SA4a, SA4b) and threshold perturbation (SA7), whereas reweighting, corpus restriction (SA2, SA4c), the small-area rule (SA5), and criterion omission (SA6) changed the number of significant contrasts (1–10 of 15); the contrast between geomagnetic and WiFi systems remained significant in all scenarios except those omitting S2 (Supplementary Material S6).

4. Discussion

4.1. Accuracy versus Infrastructure and Hardware Requirements

The pooled negative association between the positioning-accuracy score (S1) and deployment burden was driven by infrastructure density and receiver device type, did not extend to setup and maintenance complexity, and mainly reflected differences between technology classes. This narrows the accuracy–deployment trade-off described in previous reviews [3,4,74]: in this corpus, higher accuracy was associated with greater infrastructure and hardware requirements, but not with greater setup complexity.

Previous reviews describe technology-specific accuracy and propagation profiles [75] and the difficulty of evaluating several localization requirements jointly [23]. The present systematic review adds common ordinal component profiles and a separate S2–S4 burden score, allowing those relationships to be tested across technology classes while keeping validation conditions (S5) outside the burden score.

This pattern is most visible in two contrasting technological profiles. VLP/VPS systems had the lowest median S1 score in the corpus (1.0, highest accuracy) and the highest median S2 score (5.0, densest infrastructure), although 28 of these 32 systems were tested on areas smaller than 50 m^2, where the minimum number of anchors inflates device density (SA5); moreover, they were validated mainly under LOS conditions. Wang et al. [15], in a review of visible-light-based systems, describe the limited range and directionality of optical transmission as factors that may require dense placement of LED transmitters and constrain scalability. Geomagnetic and PDR/INS systems had the lowest median total five-criterion scores (2.60 and 2.80), largely reflecting their lower infrastructure scores (SA6).

Hossain and Soh [35] point to growing interest in calibration-free and infrastructure-free approaches in response to the maintenance requirements of systems using dedicated infrastructure. Naser et al. [76] describe a shift toward smartphone-centric and infrastructure-free IPS, which is broadly consistent with the descriptive profiles observed in this systematic review.

The pooled association also has a methodological implication: comparing IPS technologies solely on the basis of reported accuracy—a common practice in existing reviews [7,21]—may favor solutions with higher infrastructure and hardware requirements, even though accuracy alone does not represent the practical constraints of many deployment scenarios.

4.2. Comparison with Existing Frameworks

The EvAAL framework, used in IPIN competitions, is limited to a single performance metric (the 75th percentile of the positioning error) and does not account for deployment dimensions [30,31]. The EVARILOS Benchmarking Handbook [77] expands the set of criteria to include latency and energy efficiency and also defines deployment and functional metrics, but its benchmarks focus on system performance measured in testbed experiments and provide no scoring scheme for comparing deployment requirements across

technology classes; its adoption has been limited to a few competitions and the EVARILOS project itself [23]. ISO/IEC 18305 [29] defines test scenarios, building types, and metrics (accuracy index, startup time, fault tolerance), but it does not offer a comparative scheme covering infrastructure and configuration dimensions, and its use has been documented mainly in the PerfLoc competition [4]. Bousdar Ahmed et al. [78], in a review of testing methodologies for pedestrian localization systems, report that existing frameworks focus on positioning performance while neglecting deployment aspects.

Van Haute et al. [79] compared the performance of several IPS technologies in the same hospital environment, reporting differences in both accuracy and deployment effort. Their work illustrates the value of multidimensional evaluation but does not propose a standardized scoring scheme enabling reproducible comparisons.

Recent multidimensional IPS frameworks [4,19,26] incorporate criteria such as scalability, cost, and robustness but generally express them qualitatively. Hailu et al. [19] use low/medium/high categories, whereas Salzmann et al. [26] present a technology-integration matrix without numerical thresholds. The present scheme converts these dimensions into explicit ordinal scoring rules applied uniformly to six technology classes.

The cross-technology scope of this systematic review also distinguishes it from application-specific reviews: Wichmann [1] addresses hospital applications, and Cil et al. [32] the shipyard context.

4.3. Practical Implications

For system integrators and facility managers, the proposed scoring can support the preliminary comparison of technologies for a specific deployment scenario. When the priority is to minimize infrastructure burden, for example in rented buildings where infrastructure modification is restricted, geomagnetic and PDR/INS systems had the lowest (most favorable) median total scores, although their reported accuracy was lower than that of UWB and VLP/VPS. When centimeter- or sub-decimeter-level accuracy is required, for example in robotic applications, UWB and VLP/VPS were the classes closest to meeting such requirements in the reviewed corpus, together with higher infrastructure requirements. Technology selection should therefore consider accuracy, infrastructure burden, and end-user hardware requirements jointly rather than rely on a single error metric.

For occupancy-aware smart-building applications, the framework can support a preliminary technology selection, but position-derived lighting or HVAC control also requires reliable zone-occupancy estimates, a suitable update frequency, and integration with the building management system. In existing buildings, the deployment burden score provides a relative comparison of the infrastructure, site preparation, and dedicated hardware required for such services. Position estimates must also be referenced to the rooms and zones of the building model, which the integration of building information modeling (BIM), exchanged through the Industry Foundation Classes (IFC), with geographic information systems (GIS) can provide; Liu et al. reviewed such integration at the data, process, and application levels [80]. Isikdag et al. described the transfer of information from IFC models into a BIM-oriented indoor data model for navigation with ISO 19107-compliant geometry [81,82], and the OGC IndoorGML standard represents indoor spaces as cells with topological relations that can be linked to IFC or CityGML objects [83]. The evaluation of such integration was beyond the scope of this systematic review.

For researchers, the results reveal three gaps in the literature. First, VLP/VPS systems are validated mainly under favorable conditions, usually with an unobstructed optical line of sight and limited occlusion and environmental interference. This limits the ability to assess their usefulness in more realistic indoor scenarios involving partial occlusion, reflections, variable lighting, and challenging sensing conditions. Wang et al. [15] identify the limited optical range as a fundamental scalability challenge for VLP, yet in the

analyzed corpus only 10 of 32 VLP/VPS studies were validated under mixed LOS/NLOS or more difficult conditions (S5 ≤ 3).

Second, UWB systems, despite their increasing integration into smartphone platforms, are rarely validated on standard consumer smartphones in the analyzed corpus. Only 1 of the 35 included UWB systems used only a smartphone as the receiver device (median S4 = 3.0). Coppens et al. [84] document the increasing integration of UWB into Apple, Samsung, and Google devices and the standardization efforts of the FiRa Consortium, which points to a discrepancy between the commercial availability of UWB in smartphones and research practice, in which dedicated modules and development platforms dominate.

Third, WiFi systems were dominated by fingerprinting approaches (S3 = 4.0 in 69 of 86 studies). Shang and Wang [85] and Singh et al. [86] identify building and maintaining the radio map as a major scalability barrier, and alternative approaches, such as WiFi round-trip time/fine timing measurement (RTT/FTM) or fingerprinting-free methods based on channel state information (CSI), were less represented in deployment-oriented evaluations. Sparse-fingerprint methods, such as radio-map interpolation [87,88], crowdsourcing, and transfer learning, aim to reduce this burden; in the reviewed corpus, however, studies applying them still reported site-wide surveys with sparser reference points and were therefore scored S3 = 4. Distinguishing the density of reference points within S3 is a possible refinement of the scheme.

The results support consideration of deployment-related dimensions in future extensions of IPS testing standards such as ISO/IEC 18305 [29]. Current standards focus primarily on localization performance, while infrastructure burden, setup complexity, and end-user hardware requirements also influence real-world adoption. Comparative standards could therefore report at least infrastructure density, calibration requirements, and the receiver device class. Bousdar Ahmed et al. [78] make a similar recommendation with respect to pedestrian localization systems.

4.4. Limitations

The findings should be interpreted in light of the following limitations:

1. The search was restricted to a single database (Scopus) and to the Engineering and Computer Science subject areas. Although IEEE and ACM publications were retrieved, studies indexed only in other databases or classified only under other subject areas may have been missed. Technologies outside the six predefined classes, such as RFID, infrared, ultrasonic, and cellular positioning, were not searched as leading technologies, so the results apply only to these classes; the scoring framework could be applied to them in future work.
2. The scoring relies on data reported in publications, whose heterogeneous test environments, accuracy metrics, and reporting completeness limit comparability. RMSE or the median error was extracted for 15 records, the metric type was not recorded for 76 first-round records, and the 3D error was used for 15 records; SA4 indicated that these substitutions did not alter the S1 scores of VLP/VPS systems or the two leading rank positions. For PDR/INS, positioning error accumulates with trajectory length, which was not standardized across studies, so S1 for this class reflects the validated trajectories. The synthesis compares system profiles as reported in the included studies. No formal study-level risk-of-bias assessment was performed, so the potential influence of study-level bias on the comparisons between technology classes remains uncertain. The certainty of the evidence was not formally graded. The absence of a prespecified protocol limits independent verification of which methodological decisions were made in advance. The review documents the clarification of

the accuracy-metric eligibility rule and the expansion of the sensitivity analyses, both of which occurred during the review.

3. Data extraction was assisted by a language model, although all ambiguous cases were verified manually. Validation on a stratified sample of 60 records (39% of the first-round records) showed a low error rate; the 69 records added in the second round were not validated separately.
4. Full texts could not be obtained for 229 of the 505 records directed to retrieval. Retrieval differed by access-related characteristics, whereas no significant differences were detected for technology class or abstract-reported accuracy, which does not demonstrate independence; conference papers and recent publications are underrepresented, and characteristics not reported in abstracts, such as infrastructure density, could not be compared.
5. A rule treating each publication as one system instance was adopted, selecting the configuration validated on the largest test area. This approach simplifies the analysis and provides a clear and consistent unit of analysis, but it omits system variants reported within the same publication. A multi-instance approach could provide a fuller picture, but at the cost of greater methodological complexity and the risk of overrepresenting publications reporting multiple configurations.
6. The automated pre-screening required an explicit accuracy metric in the abstract, which increased precision but excluded potentially eligible records: the false-exclusion rate of 20% (Section 2.3) corresponds to approximately 590 (95% CI 370–860) of the 2939 automatically excluded records. Their abstract-reported position errors did not differ from those of the corpus (median 0.43 vs. 0.62 m; $p = 0.52$), but their effect on S2–S5 and on the ranking could not be determined; UWB studies, conference papers, and recent publications may be underrepresented, and PDR/INS and geomagnetic studies overrepresented.
7. The omnibus analysis was followed by Dunn's post hoc test, but the applied Bonferroni correction is conservative and, with unequal group sizes, may reduce the power of the pairwise comparisons. The lack of significance for some comparisons should therefore not be interpreted as evidence of the equivalence of the technology classes.
8. The distribution of publications across technology classes was uneven (WiFi: 86, Geomagnetic: 18, PDR/INS: 20). Smaller classes may not reflect the full spectrum of solutions of a given technology.
9. For 50 records (22.5%), the test-area size was estimated using a priori rules. Infrastructure density also depends on test-area scale, because the minimum number of anchors inflates density in small test areas, mainly for VLP/VPS and UWB, and anchor range was rarely reported, which prevented normalization. SA2 did not change the two leading rank positions; in SA5, geomagnetic systems remained first, but VLP/VPS rose to rank 2 and PDR/INS fell to rank 3 or 4, so the S2 scores of VLP/VPS and UWB, and the position of PDR/INS, are specific to the validated configurations.
10. The total applicability score should not be interpreted as a measure solely of deployability, because it also includes positioning accuracy. For this reason, the total score (S1–S5) and the deployment burden score (S2–S4) were interpreted separately in this study.
11. All criteria were assigned equal weights. Equal weighting is itself an assumption, adopted as a transparent reference point rather than as a neutral choice. The sensitivity analysis showed that geomagnetic and PDR/INS systems remained in the two leading positions under reweighting, with PDR/INS sharing second place with other classes in two scenarios, but not when S2 was omitted (SA6); the positions of the intermediate classes depended on the selected weighting priorities. The baseline score can therefore be treated as a comparative reference point within this framework, but

not as a universal preference model for all deployment scenarios. Likewise, the score thresholds are operational definitions; changing the S1 and S2 thresholds by ±20% did not alter the two leading positions (SA7).

5. Conclusions

This study proposed a five-criterion evaluation scheme for IPS, covering positioning accuracy, infrastructure density, setup and maintenance complexity, receiver device type, and the realism of validation conditions. The scheme was applied to a corpus of 222 publications from 2020 to 2025 selected in accordance with PRISMA 2020.

The findings address the research questions as follows:

RQ1: Geomagnetic and PDR/INS systems had the lowest (most favorable) median total scores, followed by UWB and WiFi and then by the BLE and VLP/VPS classes. The omnibus test indicated differences between class distributions. Within the adopted evaluation scheme, this pattern suggests that classes with lower infrastructure and hardware requirements may have lower total scores even when they do not provide the highest reported positioning accuracy.

RQ2: The largest between-class effects were observed for positioning accuracy and infrastructure density; in the pairwise comparisons, infrastructure density yielded the largest number of significant differences. Infrastructure requirements therefore appear to be an important differentiating dimension in this corpus and should be reported alongside positioning accuracy.

RQ3: The pooled moderate negative Spearman correlation suggests that higher reported accuracy often co-occurred with greater infrastructure and hardware requirements in the reviewed corpus, mainly as a difference between technology classes. This descriptive association supports evaluating IPS with deployment-related criteria in addition to positioning error, because systems with lower error may also involve greater infrastructure or hardware requirements.

Across the reweighting and data-quality scenarios, geomagnetic systems ranked first or second and PDR/INS systems first or second, in two scenarios sharing second place with UWB or VLP/VPS; these positions depended on the infrastructure-density criterion (SA6) and, for PDR/INS, on the treatment of small test areas (SA5), whereas the ordering of the intermediate classes depended on the criterion weights and should be regarded as indicative. Reporting the total score and deployment burden score separately distinguishes positioning accuracy from infrastructure, configuration, and hardware requirements. These findings should be read in light of the unequal class sizes (18 geomagnetic and 20 PDR/INS vs. 86 WiFi studies), which limit the power of the post hoc comparisons and the representativeness of the results for the smaller classes, and of the automated prescreening, which may have excluded potentially eligible records (Section 4.4).

The framework may also inform the preliminary selection of positioning technologies for mobile navigation and occupancy-aware smart-building services, while energy-related outcomes require application-specific evaluation.

Future work will proceed in two directions. The first is the further development of the proposed evaluation scheme—refining the thresholds within the individual criteria and developing weighted variants of the total score tailored to the priorities of specific application domains. The second is more extensive evaluation of infrastructure-free systems, especially geomagnetic and PDR/INS, which in this analysis had the most favorable total scores, mainly owing to their low infrastructure requirements, but have so far shown lower reported positioning accuracy in the reviewed literature.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/su182312086/s1: S1 (SM_1.xlsx), Scopus search strategies; S2 (SM_2.xlsx), bibliographic data (authors, title, source, year, and DOI) and scoring dataset for the 222 included studies; S3 (SM_3.py), deduplication script; S4 (SM_4.py), rule-based pre-screening pipeline; S5 (SM_5.pdf), structured extraction prompt and coding rules; S6 (SM_6.ipynb), reproducible statistical notebook; S7 (SM_7.xlsx), Dunn post hoc matrices and rank summaries; S8 (SM_8.md), README describing the supplementary files and how to reproduce the analysis; S9 (SM_9.xlsx), comparison of retrieved and non-retrieved reports; S10 (SM_10.md), pre-screening rules, records flagged by each rule and validation of the automated exclusions; and S11 (SM_11.xlsx), record-level results of the manual check of excluded records.

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