

# pichapol kraisak

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## **A Mobile App Based Lost and Found Information System using Smart Category Tagging and Image Matching for Central Mindanao University**

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## 1. Introduction

### 1.1. Background of the Study

Misplacement of personal belongings is an ordinary problem around the globe, but it becomes a larger problem in busy places like universities (Pede et al., 2025; Yao et al., 2019). The continuous movement and interaction of an immense community means that items are lost most of the time (Tan & Chong, 2023). Not only that it's annoying, but a serious problem that could drain resources and time. Annually, a person spends an average of 2.5 days to actively find forgotten items (Yagi et al., 2021). Recovering these items has a lower chance, as currently the systems used are inefficient and insufficient (Shrivastava et al., 2025). This kind of inadequacy shows that the retrieval remains low; for example, the recovery rate for lost mobile phones in some public places shows that only 3.2% (Jang & Kim., 2024). The need for an innovative technology-driven solution is clear, as current practices are incapable for a major institution like Central Mindanao University.

The primary reason why so many items are never returned is because of existing systems failure. Traditionally, lost and found services depend on paper logs, manual notices, or word-of-mouth which are slow, and prone to mistakes. For the administrative staff, manual logging is difficult to manage, as it could contain inaccurate documentation, inconsistency and time-consuming validation (Castro et al., 2023). Also, using informal communication channels like social media groups, results in a disordered information and exhibits security concerns as personal data becomes public (Romadhona et al., 2023). The lack of a centralized, real-time repository draws users into a time-consuming search, which directly suppresses the recovery rate of an item (Zhao & Peng., 2018).

First-generation digital solutions, like websites, are limited because they could only use basic keyword matching, which is insufficient for a large-scale retrieval as it cannot account for uncertainty, misspellings, or variations in item details. Also, there are delays in an organizations' process, because of their slow procedures, strict rules, and poor communication. To prevent this incompetence, many digitized campus solutions require manual staff verification or approval for found items posts and claims (Vasavi, 2022). The persistence lack of efficiency shows a clear need for an integrated,

intelligent platform. The system must overtake the challenge of linking unstructured human input to a specific physical object. Studies show that technology fails here because it cannot handle key areas (1) unclear descriptions and (2) visually similar items. By having a Smart Category Tagging, that could understand semantic context and close meaning of item descriptions is more plausible than keyword matching (Dhanawardhana et al., 2025).

Similarly, overcoming the limitations of visual validation requires an accurate Image Matching. Existing image models are heavy computationally for mobile devices and can be inaccurate; one the studies, for instance, reported a very low image comparison accuracy result of only 29.96% (Prawira & Saputri 2024). Therefore, the solution must combine both the semantic analysis of text and competent visual recognition which is a known process called multimodal deep learning which helps improve matching accuracy and reliability (Dhanawardhana et al., 2025). This research plans to build a smart phone app for the people at Central Mindanao University, helping fix those big problems at their core. Relying on memory, luck and manual effort is the current way of finding lost items like at CMU like checking social media groups or asking other people personally which would or could take time and often doesn't work out. A mobile app that is well designed could change that. The digitalized and ordered process helps people report and reclaim lost items securely and quicker. A campus culture would be created where the community of the CMU actively looks for the owner of a lost item. It becomes a more normal thing to do than just passing by the item. So basically, it goes beyond just returning lost items. The people realize that lost items are highly possible to find their way back to them, feeling more calm, hopeful and less stressed.

## 1.2. Statement of the Problem

Almost everyday items like identification cards, keys, wallets, or books are misplaced or lost, but still most universities continue to depend on outdated systems for managing lost and found services. Example, using manual paper logging or basic forms that just lists the items without actually tracking or any recovering mechanism. A manual process is risky as flaws are missed and is difficult to navigate, resulting in items unrecovered. New technological innovations like image-based matching, smart tagging, and smartphone-derived geolocation are often ignored. This gap shows the

clear potential benefits of the creation of a mobile application that not only reports losses but also actively helps users recover their lost items efficiently and with minimal effort.

### **1.3. Research Objective**

#### **1.3.1. General Objective**

To design and develop a mobile-based lost and found application using smart tagging, image recognition, and location-based tracking.

#### **1.3.2. Specific Objectives**

1. To help users recover and locate their lost items by implementing real-time notification and tracking systems.
2. To implement an administrative feature to verify recovered and manage reported items.
3. To evaluate the system's effectiveness and usability by testing and user feedback.

### **1.4. Scope and Limitations**

This section states the limits of this research, what it includes, and the needed restraints that can affect the implementation and the final result's usefulness. The scope ensures that the project is feasible within the allotted time and resources, while the limitations set realistic expectations for the system's behavior and reach.

#### **1.4.1. Scope of the Study**

The main focus of this study is to design, develop and initial evaluation of a secure, mobile-based Lost and Found Information System specifically custom for the academic community of Central Mindanao University (CMU). The scope is centered to satisfy the general objective of the study: to create a comprehensive digital platform that would use smart technologies to modernize item recovery. This involves the following specific elements:

1. The system delivers a mobile application designed as the single, centralized interface for all users within the community. This application serves both end-users

- (students, faculties and staff) in reporting lost and found items, and an authorized CMU administrative personnel for managing reports and verifying items (Castro et al., 2023).
2. To improve the system's precision a multi-modal matching technology is included as one of the cores of the system (Dhanawardhana et al., 2025). It Contains:
    - Smart Category Tagging: Using Natural Language Processing or NLP principles to analyze unclear text descriptions and categorize them items for searching precision.
    - Image Matching: Deploy a light deep learning model to help extract visual features from uploaded images, allowing the system to match items that look similar, regardless of minor versions in the images (Zhou et al., 2024).
  3. The application includes key features to help for efficient recovery, which basically addresses the specific objectives:
    - The system is implemented to generate push notifications for potential matches and record item locations using the user's device Global Positioning System (GPS) at the time of reporting (Arbat et al., 2025; Prashanth et al., 2025).
    - For a secure authentication, institutional credentials are used for role-based access for administrative staff and general users which will be in a module.

#### **1.4.2. Limitations of the Study**

The constraints below are accepted and recognized to ensure the project is still feasible and manageable:

1. The result of this study and the system implementation is focused only on and limited to the user population and the institutional environment of the Central Mindanao University. The findings may not be generalizable to

external environments or other institutions. (Koç et al., 2016). The development only prioritizes a mobile operating system (Android) for the pilot phase. (Castro et al., 2023; Tan & Chong, 2023).

2. The functionality for "location-based tracking" relies solely on standard commercial Global Positioning System (GPS) capabilities and does not extend to highly accurate indoor positioning systems (IPS). Implementing and maintaining specialized hardware, like Bluetooth Low Energy (BLE) beacons or other tracking infrastructure needed for accuracy inside buildings, is outside the project's resource and time boundaries (Khruahong et al., 2018; Shoji & Ohno, 2022).
3. Intelligent matching engine relies on a multimodal approach that is combined within the Siamese Networks that uses MobileNetV2 for image matching. Preferred semantic text matching if the SBERT (Sentence-BERT) model is preferred as it can quickly compare text similarities (Dhanawardhana et al., 2025; Zhou et al., 2024). This kind of architecture may actually sacrifice maximum accuracy achievable computationally heavier models but optimized for speed and compatibility to mobile devices (Prawira & Saputri, 2024). The model's extraction capability for image matching can also degrade as it depends on the external user factors, like low-quality photos, low-light conditions, and blurry images (Ghazal et al., 2015; Zhou et al., 2024). Semantic tagging's initial performance relies on the variety of the item dataset that is collected. (Dhanawardhana et al., 2025).
4. Item verification and handover is explicitly for manual administrative approval, this is necessary to maintain institutional accountability that would prevent fraudulent activities. Due to this the overall effectiveness of the system cannot be achieved 100% (Vasavi, 2022). In

addition the tight budget, basic tests for user access and login systems are the sole security checks in this project. In-depth checks and hacking simulations are not covered (Sultan et al., 2021).

### **1.5. Significance of the Study**

By utilizing advanced technology in creating a reliable, and secure recovery solution for the Central Mindanao University(CMU) community. This research provides a remarkable value that helps to address the lost item recovery efficiency of an academic environment. The foremost beneficiary is the CMU community, including students, faculty, and administrative staff. This application provides relief from lengthy issues of manual and inefficient reporting, which currently results in a low recovery rate and the lost amount of time (Yagi et al., 2021; Shrivastava et al., 2025). It offers a smooth method for urgent report of lost or found items, with last location and description details. Users are quickly alerted when there's a possible match occurrence by the integration of a real-time notification and intelligent matching (Prashanth et al., 2025). It significantly increases the overall rate of recovery for an individual's lost belongings and decreases or avoids the time wasted searching for these items. The institutions gain a unified, auditable and secure administrative tool (Sinha et al., 2024). Automation of the preliminary matching and tracking reduces manual workload like sorting, logging, and validation of reports. This change allows the administrative time and resources to be focused toward core institutional functions, which helps to make operations become efficient. Based-role security and verification modules ensure the data integrity and accountability for the returning process which mitigates the possible fraud. (Vasavi, 2022).

This research focuses on the integration of smart category tagging, which retrieves the meaning by analyzing unstructured text. Another is image matching for visual recognition. Deep learning is the main component and can be bundled with a mobile app (Dhanawardhana et al., 2025; Yao et al., 2019). This way of integration moves beyond the limitations of basic keyword searches, which provides a measurable increase in matching accuracy and the effectiveness of the system that most campus solutions lack. If the designing, developing, and evaluation of this complex, intelligent system within the defined CMU environment is successful. This

study provides a clear plan for future research. It connects artificial intelligence (AI) models to practical use in mobile apps. Other universities can trust the app's benchmarking from the collected test data for usability and performance in improving their lost and found services. By digitalizing the campuses, this project aligns with the trend of the world. Institution services should adapt an efficient, secure and modern technology to transition from outdated processes. This new standard, makes educational institutions leverage modern mobile and AI technology which improves communities welfare and streamline organization management.

## **2. Review of Related Literature**

### **2.1. Abstract**

Losing personal items remains a significant challenge in universities and public spaces, where current lost-and-found systems depend on keyword searches and subjective descriptions, leading to low recovery rates. This scoping review has methodically reviewed 60 studies (2015–2025) focused on mobile-based lost-and-found systems that make use of smart tagging and image recognition technologies. The PRISMA framework guided the exploration of literature from searching academic databases to creating a map of existing architectures, methodologies, performance outcomes, and research gaps. The results to date show the existence of two major research areas: AI-based matching and retrieval (37%), where deep learning techniques dominate the scene, including CNNs, Siamese networks, Sentence-BERT, and perceptual hashing for multimodal similarity detection; and digital platform development (33%), concerned with web/mobile applications that offer basic categorization and reporting functions. Although there has been a fast development in computer vision, major problems are still left, among them limited field testing, no standard benchmarks, and not enough usability testing along with scalability challenges and lack of sensitivity to users' privacy and security concerns

### **2.2. Methodology**

#### **2.2.1. Literature Profiling Methodology**

The papers used for this review were from academic databases namely IEEE Xplore, ERIC, Web of Science, ACM Digital Library, and Google Scholar.

For searching, research objectives were broken down into key concepts. These were then combined using Boolean operators. The table below shows strings used for each concept.

**Table 1.** Search Strings Table

Keywords	Search Strings
Lost and Found Systems	("lost and found" OR "lost item*" OR "missing object*") AND ("system" OR "management" OR "recovery") OR ("found property" AND "lost property")
Mobile-Based Information Systems	("mobile app" OR "smartphone application") AND ("information system" OR "platform") OR ("mobile-based system" AND "app-based") AND ("lost and found" OR "item recovery" OR "object retrieval")
Smart Category Tagging	("smart tag*" OR "RFID tag" OR "NFC tag" OR "Bluetooth beacon" OR "QR code tag") AND ("category" OR "labeling") OR ("smart labeling" AND "tagging")
Image Recognition Technologies	("image recognition" OR "image matching" OR "computer vision" OR "object detection" OR "visual search" OR "image-based identification") AND ("lost and found" OR "item recovery" OR "object retrieval")
Location Tracking Mechanisms	("object tracking" OR "item locator" OR "asset tracking") AND ("location" OR "geolocation" OR "proximity") OR ("detection service" AND "locator")

AI and Machine Learning	("artificial intelligence" OR "machine learning") AND ("deep learning" OR "neural network*") OR ("AI model" AND "learning")
User Adoption and Effectiveness	("user adoption" OR "system usability") AND ("accuracy" OR "recovery efficiency") OR ("adoption factor*" AND "effectiveness")
Ethical and Privacy Considerations	("privacy concern*" OR "user privacy") AND ("data security" OR "ethical issue*") OR ("scalability challenge*" AND "privacy")

To ensure the results from these searches were relevant, a clear set of rules were used to decide which papers to include. These criteria are detailed in the table below.

**Table 2.** Criteria Table

Criteria	Inclusion	Exclusion
Publication years	2015 - present	2014 and below
Language	English	Non-English
Document Type	Peer-reviewed article papers, journal articles, dissertations, theses, and conference papers	Opinion papers, blogs, non-scholarly papers, editorials, and commercial materials
Methods	Studies applying mobile applications, smart category tagging, or image	Papers lacking methodological details or papers that discuss personal opinions

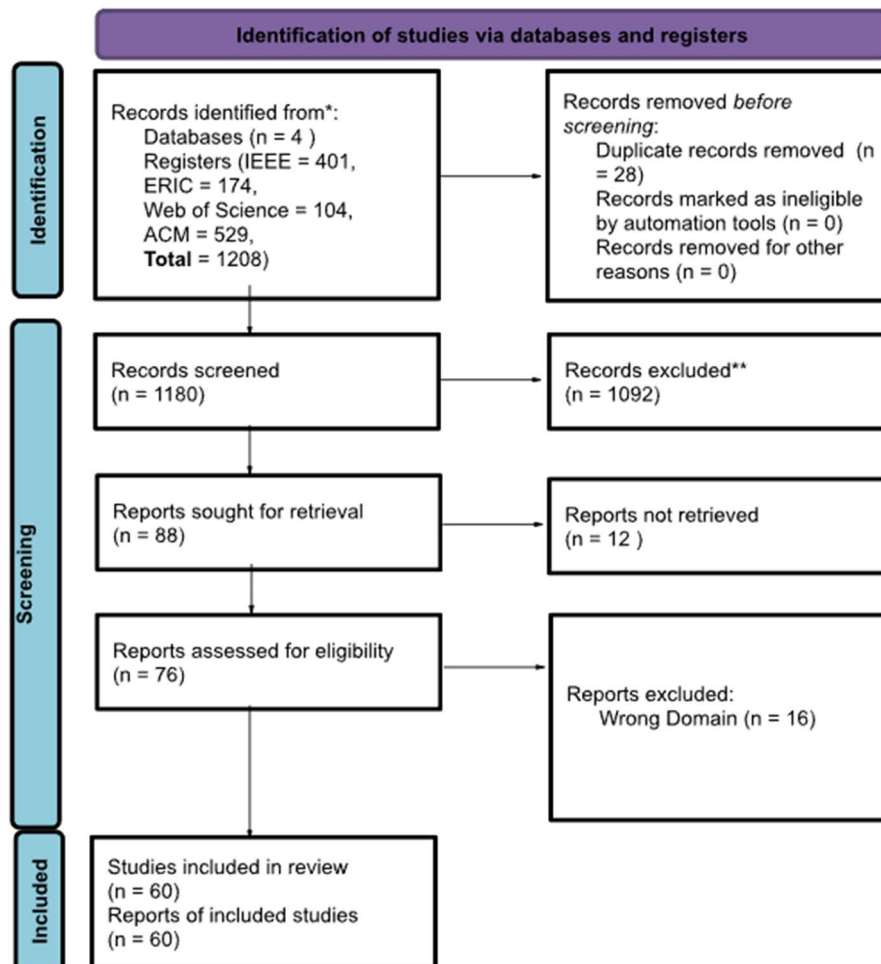
	recognition technologies	
Full Text	Available in downloadable PDF or accessible full text	Abstract-only or unavailable full text
Relevance to Topic	Focused on lost and found systems, image matching, or tagging-based mobile systems	Studies unrelated to lost and found or not involving smart technology
Application Context	Research in academic, institutional, or public service environments	Studies in commercial, industrial, or unrelated private sectors

The search results were exported as CSV files and imported into Zotero for deduplication. During this step, 28 duplicates (2.3%) were detected and removed, leaving 1,180 unique papers for screening. The studies then underwent a two-phase screening process with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework.

In the first screening phase, titles and abstracts were examined, resulting to the exclusion of 1,092 records that failed to meet the inclusion criteria. This left 88 studies for full-text review, but only 76 were eligible because some full papers could not be accessed.

The second phase consisted of full-text screening to exclude studies that were not in the intended domain. Therefore, 16 papers were removed, as they were in the wrong domain.

After completing all screening stages, 60 studies were retained for the final review. Refer to the PRISMA Diagram below.



**Figure 1.** PRISMA Diagram

The data extraction matrix was developed through a structured process. First, papers were assigned individually, thus, each author reviewed 20 sources in detail. During this review, qualitative and quantitative data was collected from each paper. The extracted data included the author, a brief summary of the study's focus, the identified problem, objectives, methodology, results, contributions, and stated limitations.

The process also recorded the paper's DOI, and secured the complete PDF or full text.

### 2.2.2. Scoping Analysis Methodology

The scoping analysis began with examining the description, problem, and objectives columns in the journal assessment matrix. During this phase, themes, methodologies, and application areas were identified. A codebook was developed which contained labels representing each study.

These codes were then reviewed and categorized based on similarity to form broader themes. These themes represent the methodological approaches observed in the study, such as Hardware-Based Tracking (Hamidi et al., 2023; Dr. Immaculate & Dr. Latha 2017; Nadeem et al., 2021), AI-Driven Matching & Retrieval (Yao et al., 2019; Jang & Kim 2024; Zhang & Hu 2021; Pang et al., 2018; Yagi et al., 2022; Dhanawardhana et al., 2025; Meenalochini et al., 2018; Patil et al., 2024; Sivakumar et al., 2021; Bruno 2021; Singla et al., 2023; Hassan et al., 2024; Ghazal et al., 2015; Zhou et al., 2021; Prawira & Saputri 2024; Khan et al., 2022; Karma & Darma 2025; Ma et al., 2019; Liu et al., 2018; Konda 2025; Ghaleb et al., 2022;) , and Location-Based (GIS) Systems (Prashanth et al., 2025; Hang & Shuangyun 2018; Abraham et al., 2023) .

The categorization process was conducted with the help of Google Sheets PivotTable, which was also responsible for producing charts that showed the frequency and distribution of these themes visually.

The sub-themes were formed as a result of the evaluation of the results column of the matrix, which was done following the main themes. The sub-themes are more detailed descriptions of the results, the trends observed, the specific features of the system, and the common outcomes of the evaluation reported for each theme. To illustrate, the studies in the Hardware-Based Tracking theme were characterized by the reported results during the analysis indicating Signal Performance (Dr. Immaculate & Dr. Latha 2017; Nadeem et al., 2021) as an example, such as findings on accuracy of RSSI (Shoji & Ohno 2022; Nadeem et al., 2021) its range, etc., or User Usability (Hamidi et al., 2023), such as results from SUS scores or user feedback surveys. With this two-level analysis, a structured synthesis of the technologies used, their performance, and their effectiveness was possible.

### 2.2.3. Methodological Analysis Methodology

The Methodology column was examined from a different angle in order to understand the methods applied in every single study. The review team first read the Methods section of each article and wrote down important details in the Journal Assessment Matrix. To achieve uniformity and trustworthiness, the papers chosen were reviewed by another team member, and any differences were solved through conversation. Subsequent to this, the Journal Assessment Matrix was expanded to include new columns specifically for methodology reporting, which included the highest-level method category (Method L1), the technique applied (Method L2), and separate columns for evaluation metrics, tools or platforms, and datasets.

Each paper was coded onto the matrix through a two-step procedure. First, the reviewers assigned each research under a Method L1 (Family) based on its main approach. After that, the specific method or technique was recorded under Method L2 in the respective family. Among these categories were the datasets' types that were used for training and testing like custom-collected image sets, public benchmarks, the machine learning models that were used like CNNs (Hassan et al., 2024; Ma et al., 2019; Liu et al., 2018; Ghaleb et al., 2022; Sivakumar et al., 2021; Yagi et al., 2022;), Siamese networks (Dhanawardhana et al., 2025; Liu et al., 2018), the IoT frameworks or hardware protocols that were used like Bluetooth (Hamidi et al 2023; Khruahong et al., 2018; Sun et al., 2015; Nadeem et al., 2021), RFID (Aiman et al., 2021; Ghazal et al., 2015; Ghazal et al., 2016), LoRa (Shoji & Ohno 2022; Nadeem et al., 2021) , and the software development practices that were referred to like Agile (Dhawal et al., 2025; Arbat et al., 2025; Muhammad-Bello et al., 2022), Waterfall (Romadhona et al., 2023).

After the classification process, the trends in different methods were summarized. This was done through the use of Google Sheets PivotTable to count how often each method was applied. These tables were then used to generate visualizations on the distribution of methods, such as which machine learning models or IoT frameworks were most prevalent in the literature. The team then proceeded to complete the remaining columns for metrics, tools/platforms, and datasets. The metrics column detailed the performance measures or evaluation criteria used in each

study, the tools/platforms column listed the programming languages, software tools, or frameworks applied.

#### **2.2.4. Research Gap Analysis Methodology**

Research gaps were identified through a systematic review of three different sources within the extracted data. Topical gaps representing unaddressed problem areas or overlooked user groups were identified from the problem statements of the included papers. Methodological gaps were identified from the Methodology sections. Finally, evaluation gaps were derived from the stated results and limitations sections, which points to the weaknesses in how systems were tested, such as a lack of real-world deployment, small sample sizes, or missing usability assessments.

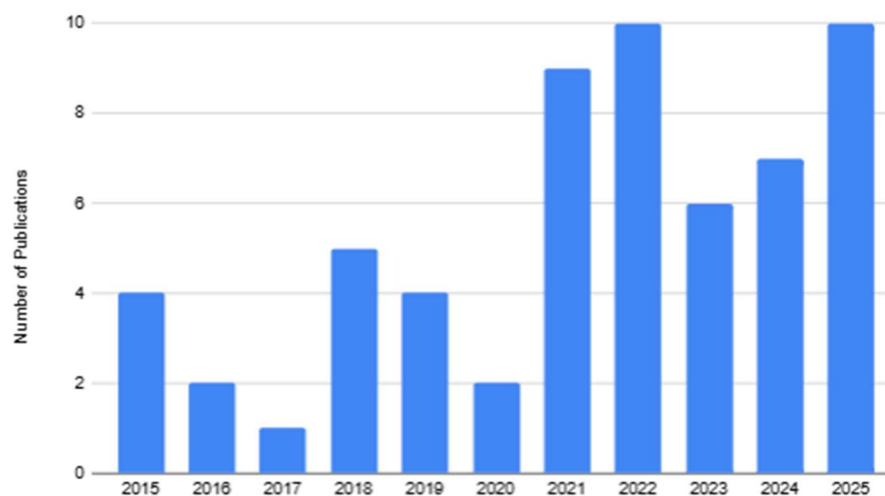
Identifying the gaps was the first step of the analysis, and the gaps were then labeled with descriptive codes. These codes were organized into several categories according to their essential meaning, such as lack of scalability testing, over-reliance on simulation, privacy concerns not addressed. The next step was to count these categories, which reflected the frequency of each gap and revealed the most typical flaws in the existing literature.

A mapping process was carried out to draw conclusions from these findings. The recognized research gaps were compared with the main themes set during the scoping analysis. Such a mapping made it possible to see clearly the connection between the themes that are being worked on and the gaps that the researchers are willing to fill.

### **2.3. Results and Discussion**

#### **2.3.1. Literature Profiling Results**

The analysis of the 60 included studies was performed through the examination of their publication year, country of origin, application domain, and their primary research theme.



**Figure 2.** Publication Trends Over Time.

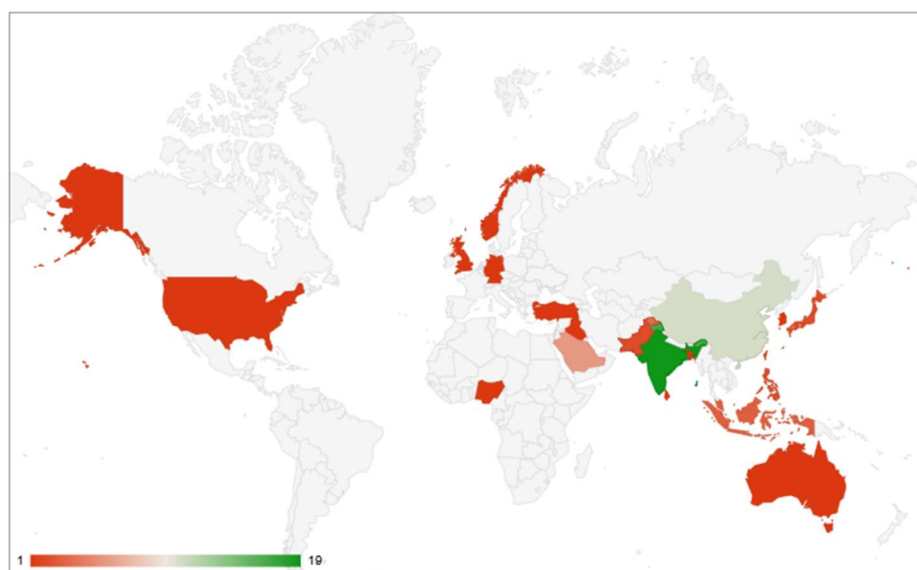
The included studies' publication years distribution is illustrated in figure 2. The various levels of research activity are indicated for the years 2015-2025. The years 2022 and 2025 had the same number of studies - 10 (16.67%) while 9 (15%) studies belong to 2021. The year 2018 had five (8.33%) publications. 2024 had 7 studies (11.67%), while the early years of 2016 and 2017 had the lowest contribution of 2 and 4 publications, respectively.

The interest in the topic is still there, but the levels are not constant as they go down and up, with 2025 being the year with the highest number of publications, ten papers in total. This points out gradually increasing scholarly and practical interest in mobile-based lost and found systems for the past few years.

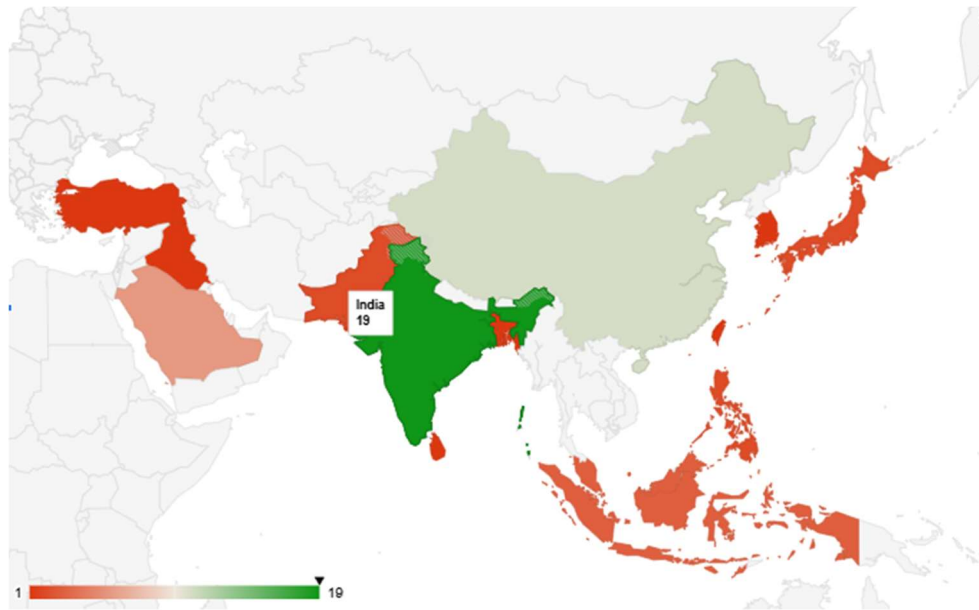
**Table 3.** Distribution of Papers by Publication Year

Year	Count	Paper IDs
2015	4	[14], [24], [44], [56]
2016	2	[26], [45]

2017	1	[13]
2018	5	[9], [10], [20], [28], [57]
2019	4	[3], [5], [15], [55]
2020	2	[17], [29]
2021	9	[7], [19], [30], [32], [34], [46], [48], [50], [51]
2022	10	[11], [12], [22], [33], [39], [40], [43], [52], [59], [60]
2023	6	[1], [8], [21], [37], [38], [42]
2024	7	[4], [6], [16], [25], [31], [41], [49]
2025	10	[2], [18], [23], [27], [35], [36], [47], [53], [54], [58]
<b>Total</b>	<b>60</b>	



**Figure 3.** Geographical and Domain Distribution (World)



**Figure 3a.** Geographical and Domain Distribution (Asia)

The country distribution of the 60 studies included in this scoping review shows a wide range of mobile-based lost and found system research across the globe. The studies are primarily from Asia that accounts for 53 (85%) papers of the total studies, while the remaining 7 studies (15%) could be found in Europe, Africa, and Oceania. Among the major researchers from Asia, India ( $n = 19$ ; 31.7%) and China ( $n = 10$ ; 16.63%) were the highest contributors, then followed by Saudi Arabia ( $n = 6$ ; 10%), Indonesia ( $n = 3$ ; 5%), and Malaysia ( $n = 4$ ; 6.67%).

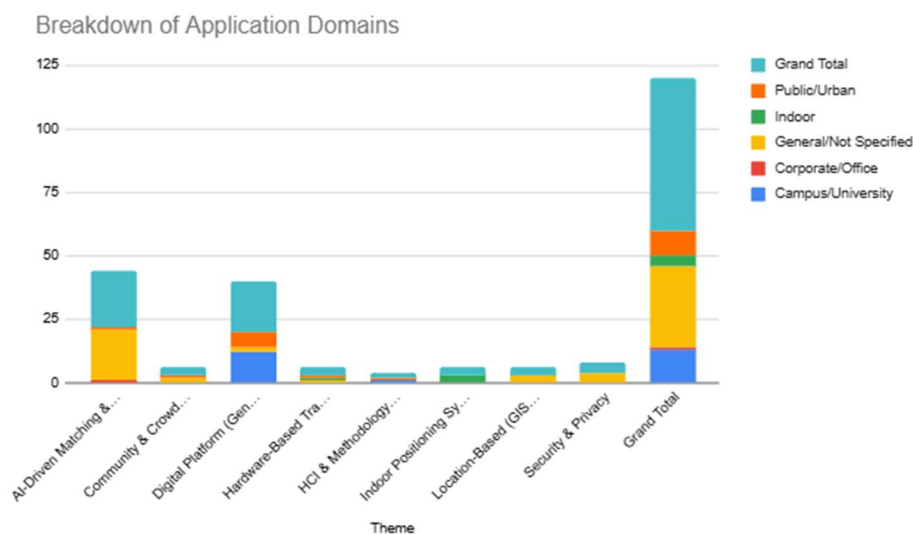
The distribution is indicative of a global effort to improve the lost and found systems and to make them more innovative through the use of technology.

**Table 4.** Geographical Distribution of Studies

Country	Count	Paper IDs
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India	19	[2], [4], [5], [13], [16], [18], [23], [25], [28], [31], [32], [33], [35], [36], [37], [38], [47], [51], [60]
China	10	[3], [10], [14], [19], [20], [29], [30], [46], [55], [57]
Saudi Arabia	6	[17], [44], [45], [48], [59], [24]
Indonesia	3	[8], [49], [54]
Malaysia	4	[1], [21], [53], [56]
Bangladesh	1	[50]
Germany	1	[42]
Iraq	1	[39]
Japan	2	[12], [22]
Nigeria	1	[43]
Norway	1	[41]

Pakistan	2	[7], [52]
Philippines	2	[11], [40]
Sri Lanka	1	[27]
United Kingdom	1	[34]
USA	1	[58]
Turkey	1	[26]
South Korea	1	[6]
Australia	1	[9]
Taiwan	1	[15]
<b>Total</b>	<b>60</b>	



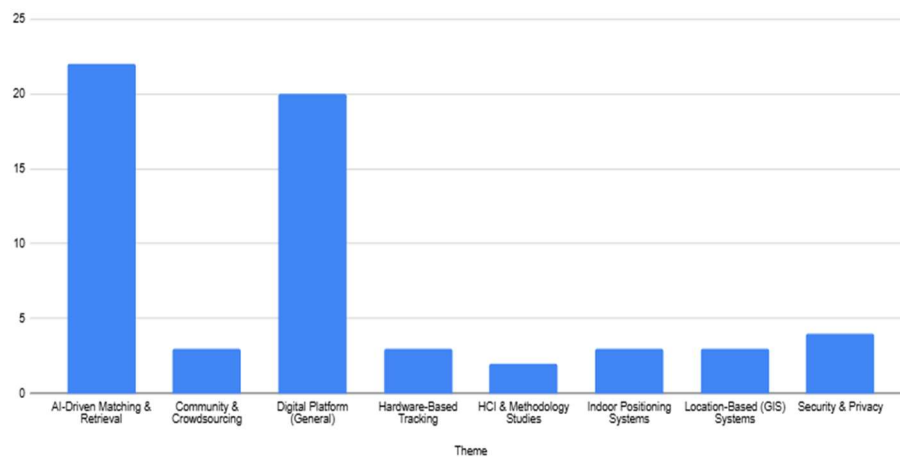
**Figure 4.** Application Domains by theme.

Figure 4 breaks down the application domains mentioned. It shows that most of the studies (n=32, 53%) were included in the category of 'General/Not Specified,' which implies that these were solutions meant for the public in general, and there was no particular target environment. The second domain was 'Campus/University' settings (n=13, 22%), and this shows that there is a necessity for such systems in educational institutions. This was then followed by 'Public/Urban' areas (n=10). The specialized domains such as 'Indoor' (n=4) and 'Corporate/Office' (n=1) were not as common.

**Table 5.** Distribution of Studies by Application Domain

Domain	Count	Paper IDs
General/Not Specified	32	[2], [3], [7], [10], [13], [14], [16], [18], [19], [20], [22], [27], [28], [29], [30], [31], [32], [34], [35], [36], [37], [38], [41], [44], [45], [46],

		[49], [52], [54], [55], [57], [59]
Campus/University	13	[4], [5], [8], [11], [21], [23], [24], [25], [26], [40], [47], [53], [60]
Public/Urban	9	[6], [17], [33], [39], [42], [43], [48], [50], [51], [56]
Indoor	4	[1], [9], [12], [15]
Corporate/Office	1	[58]
<b>Total</b>	<b>60</b>	



**Figure 5: Distribution by Research Theme**

The coding of the primary research theme is presented visually in Figure 5. The two themes with the highest frequency were 'AI-Driven Matching & Retrieval' (n=22, 37%) and 'Digital Platform (General)' (n=20, 33.3%). These two themes together represent 42 out of the total 60 studies (70%). There is a major concentration either on the

technological aspects of the underlying matching (like image recognition) or on the digital systems (like websites or mobile apps) development.

Smaller, more specialized themes form the remainder of the research. These include 'Security & Privacy' (n=4), and clusters of three studies each in 'Hardware-Based Tracking' (e.g., Bluetooth, RFID), 'Indoor Positioning Systems,' 'Location-Based (GIS) Systems,' and 'Community & Crowdsourcing.' 'HCI & Methodology Studies' (n=2) represent a focus on usability and user experience methods.

**Table 6.** Distribution of Studies by Primary Research Theme

Theme	Count	Paper IDs
AI-Driven Matching & Retrieval	22	[3], [6], [19], [20], [22], [27], [28], [31], [32], [34], [38], [41], [44], [45], [46], [49], [52], [54], [55], [57], [58], [59]
Digital Platform (General)	19	[4], [5], [8], [11], [17], [18], [21], [23], [24], [25], [33], [36], [39], [40], [43], [47], [50], [53], [56], [60]
Security & Privacy	4	[7], [14], [29], [30]
Hardware-Based Tracking	3	[1], [13], [48]
Indoor Positioning Systems	3	[9], [12], [15]
Location-Based (GIS) Systems	3	[2], [10], [37]

Community & Crowdsourcing	3	[16], [35], [51]
HCI & Methodology Studies	2	[26], [42]
<b>Total</b>	<b>60</b>	

### 2.3.2. Scoping Analysis Results\

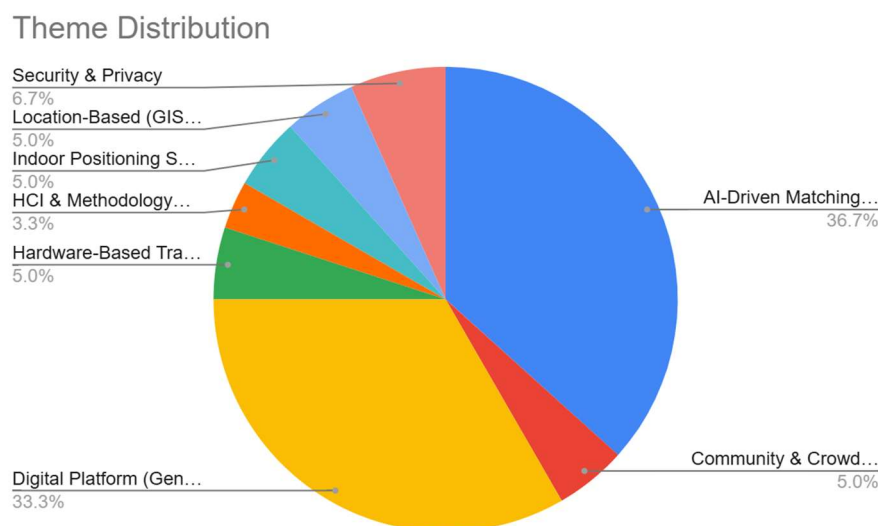
This section presents the main themes and sub-themes that emerged from the coding of the description, problem, and objectives components of the 60 reviewed studies. The analysis classified the studies into eight distinct thematic categories.

The classified themes of the 60 studies show that AI-Driven Matching & Retrieval (Yao et al., 2019; Jang & Kim 2024; Zhang & Hu 2021; Pang et al., 2018; Yagi et al., 2022; Dhanawardhana et al., 2025; Meenalochini et al., 2018; Patil et al., 2024; Sivakumar et al., 2021; Bruno 2021; Singla et al., 2023; Hassan et al., 2024; Ghazal et al., 2015; Zhou et al., 2021; Prawira & Saputri 2024; Khan et al., 2022; Karma & Darma 2025; Ma et al., 2019; Liu et al., 2018; Konda 2025; Ghaleb et al., 2022;) (n = 22; 36.67%) and Digital Platform (General) (Sudhanshu et al., 2024; Tiwari et al., 2019; Romadhona et al., 2023; Castro et al., 2022; Alnaghaimshi et al., 2020; Dhawal et al., 2025; Tan & Chong 2023; Krishna et al., 2025; Bataineh et al., 2025; Abraham et al., 2024; Kumar et al., 2022; Shrivastava et al., 2025; Salman & Athab 2022; Castro et al., 2022; Muhammad-Bello et al., 2022; Pede et al., 2025; Hossain et al., 2021; Shahzan & Arbaiy 2025; Saemi et al., 2015; Vasavi et al., 2022) (n = 20; 33.33%) were the most dominant research themes. Together, these two themes account for 42 of the 60 studies (70%), indicating a strong focus on either the underlying matching technology or the development of comprehensive digital systems.

The remainder of the research was categorized under smaller, more specialized themes. These include Security & Privacy (Aiman et al., 2021; Sun et al.,

2015; Zhang et al., 2020; Xu et al., 2021) ( $n = 4$ ; 6.67%), and several clusters of three studies each (5%): Hardware-Based Tracking (Hamidi et al., 2023; Dr. Immaculate & Dr. Latha 2017; Nadeem et al., 2021), Indoor Positioning Systems (Khruahong et al., 2018; Shoji & Ohno 2022; Chen & Liu 2019), Location-Based (GIS) Systems (Prashanth et al., 2025; Hang & Shuangyun 2018; Abraham et al., 2023), and Community & Crowdsourcing (Choudhary et al., 2021; Dutta et al., 2024; Arbat et al., 2025). The smallest theme was HCI & Methodology Studies (Koc et al., 2016; Keusch et al., 2021) ( $n = 2$ ; 3.33%). Figure 5 presents this thematic distribution across the included studies.

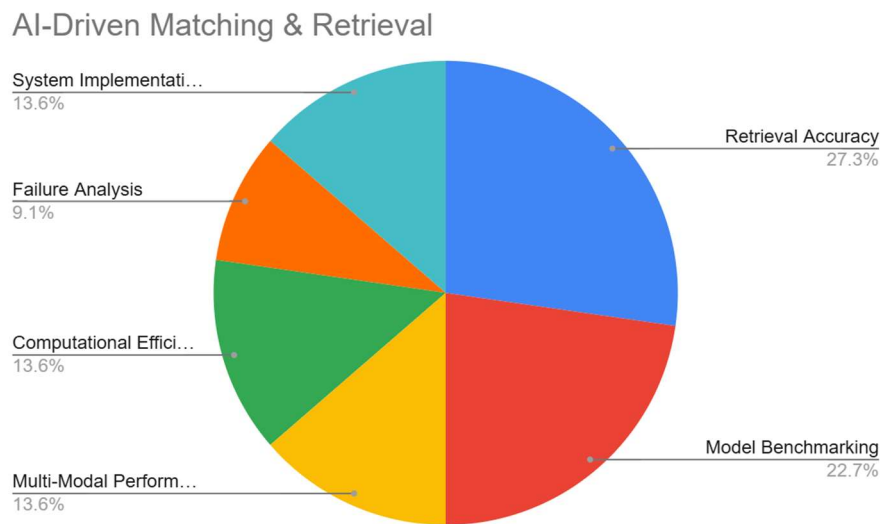
**Figure 6.** Publications included by classified theme across all studies ( $n=60$ ).



### 1. AI-Driven Matching & Retrieval

The studies in this group concentrated on developing “smart” systems that apply artificial intelligence to automatically pair lost items with those that were found. Since these systems had to demonstrate the effectiveness of their AI models, the findings were largely centered on performance results. A number of papers reported clear retrieval accuracy results (Meenalochini et al., 2018; Patil et al., 2024; Bruno 2021; Singla et al., 2023; Zhou et al., 2021; Prawira & Saputri 2024) (6 papers, 27.27%). Others compared their models against existing baselines through model benchmarking (Pang et al., 2018; Sivakumar et al., 2021; Ma et al., 2019; Liu et al 2018; Ghaleb et al., 2022) (5 papers, 22.73%). Several explored multi-modal performance (Yao et al., 2019; Dhanawardhana et al., 2025; Ghazal et al., 2016) (3 papers, 13.64%), combining techniques such as text and image matching. Some

studies focused on computational efficiency (Aiman et al., 2021; Sun et al., 2015, Zhang et al., 2020) (3 papers, 13.64%), measuring speed or memory usage. A smaller portion offered failure analysis (Jang & Kim 2024; Karma & Darma 2025) (2 papers, 9.09%), discussing why mismatches occurred. The rest confirmed full system implementation (Yao & Kun 2024; Chen & Liu 2019; Yagi et al., 2022) (3 papers, 13.64%), showing that the AI was not only theoretical but deployed inside a working system.

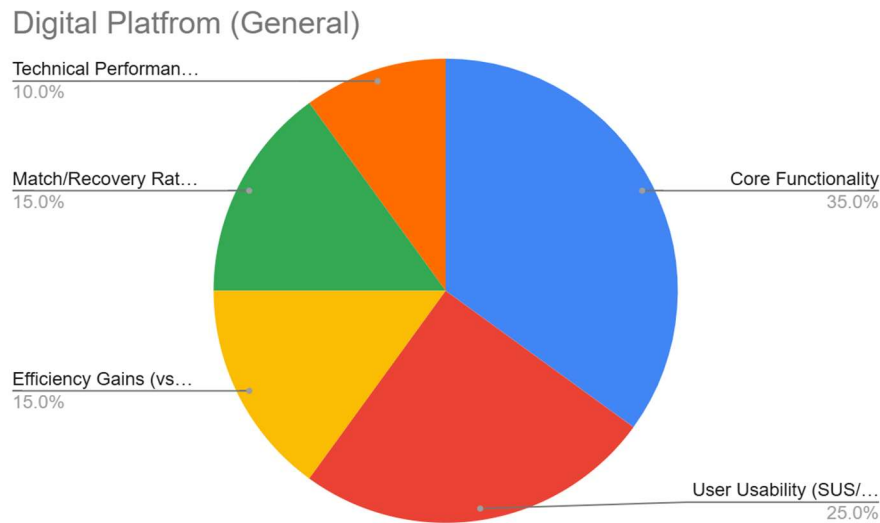


**Figure 7.** Distribution of per sub-them of the theme AI-Driven Matching & Retrieval (22 publications)

## 2. Distribution of per sub-them of the theme AI-Driven Matching & Retrieval (22 publications)

This theme covered systems that aimed to modernize lost-and-found reporting using web or mobile applications. Rather than advanced AI, the platform itself was the main innovation. Most studies demonstrated working core functionality (7 papers, 35%). Several evaluated user usability, often using surveys or SUS scores (Muhammad-Bello et al., 2022; Romadhona et al., 2023; Castro et al., 2022; Bataineh et al., 2015; Tan & Chong 2023) (5 papers, 25%). Others reported efficiency gains over manual reporting (Dhawal et al., 2025; Shrivastava et al., 2025; Sudhanshu et al., 2024) (3 papers, 15%), showing faster response times or fewer errors. Some measured match or recovery rates (Pede et al., 2025; Krishna et al., 2025; Abhiram et al., 2024) (3 papers, 15%) to show practical effectiveness. The smaller group assessed the

technical performance from the server's perspective (Arbet et al., 2025; Krishna et al., 2025) (2 papers, 10%), like page load speed and database response time.

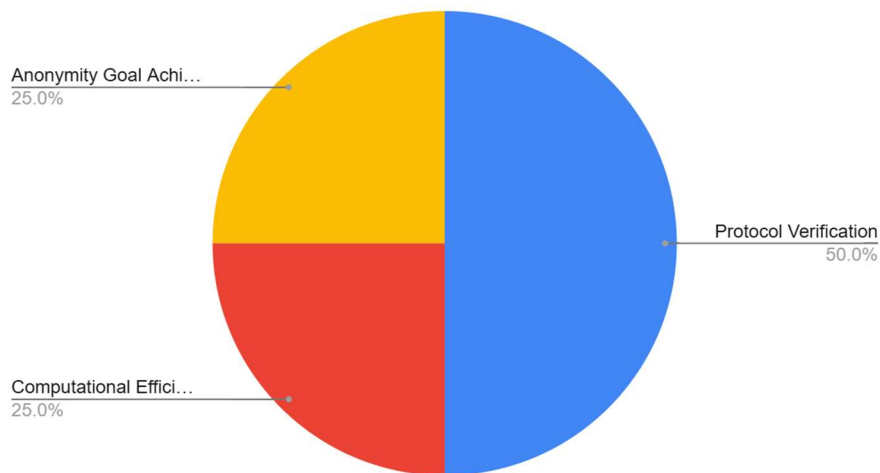


**Figure 8.** Distribution of per sub-them of the theme Digital Platform (20 publications)

### 3. Security & Privacy

The research prioritized users' sensitive data protection and safe communication between users and devices. The formal protocol verification was performed in two papers (Xu et al., 2021; Sun et al., 2015 ) out of four contributors (50%), who were able to give a mathematical proof of the security claims of the system. Aside from that, another study aimed for the anonymity goals (Aiman et al., 2021) (1 paper, 25%); it pointed out that user assistance in the process of locating objects could be provided without exposing personal information.

### Security & Privacy

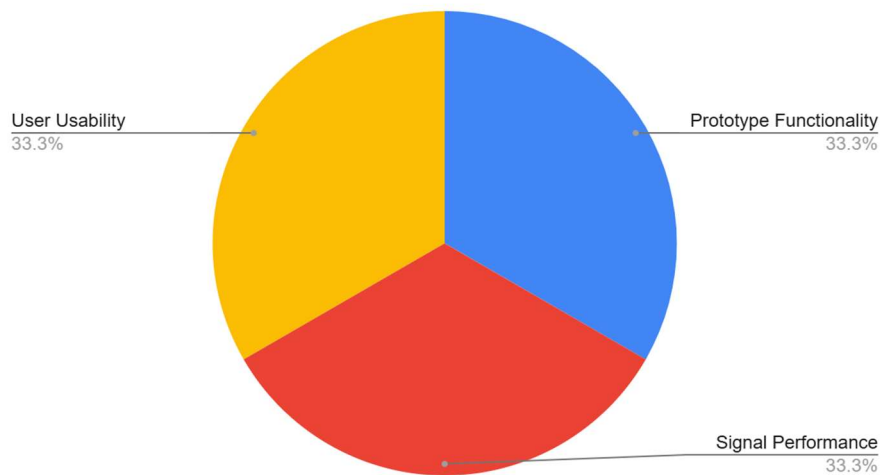


**Figure 9.** Distribution of per sub-them of the theme Security & Privacy (4 publications)

### 4. Hardware-Based Tracking

The studies concentrated on the physical tracking tags which generally relied on Bluetooth or RFID technologies to assist customers in finding their belongings. The findings comprised working models (Dr. Immaculate & Dr. Latha 2017) (1 paper, 33.33%), testing of signal characteristics like range and stability (Nadeem et al., 2021) (1 paper, 33.33%), and user opinions about the gadget and software combination through hands-on contact (Hamidi et al., 2023) (1 paper, 33.33%).

### Hardware-Based Tracking

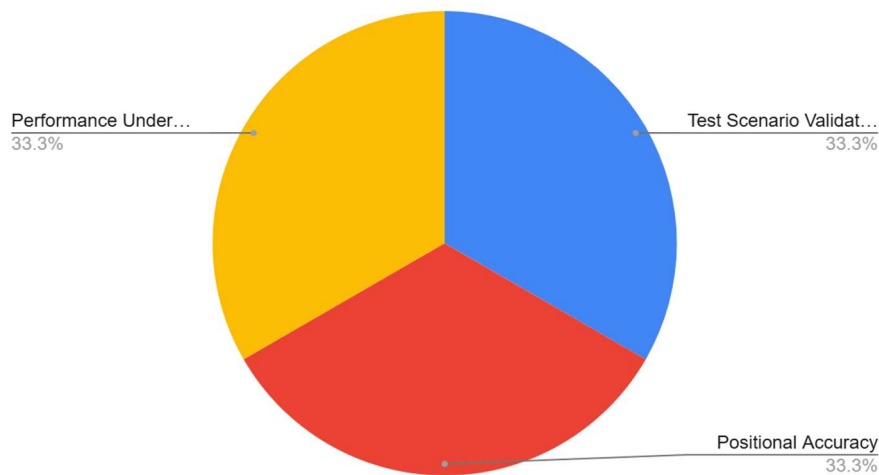


**Figure 10.** Distribution of per sub-them of the theme Hardware-Based Tracking (3 publications)

## 5. Indoor Positioning Systems

These studies were directed towards finding objects inside buildings, where regular GPS signals do not reach. The findings indicated a successful verification in real indoor environments, thereby proving that the proposed concept worked well (Chen & Liu 2019) (1 paper, 33.33%). Other researchers estimated the accuracy of the location (Khruahong et al., 2018) (1 paper, 33.33%). One of the studies checked the performance of the system in the presence of obstructions (Shoji & Ohno 2022) (1 paper, 33.33%), and it was found that the system was still working when the signal path was blocked by physical barriers like walls or metal objects.

### Indoor Positioning Systems

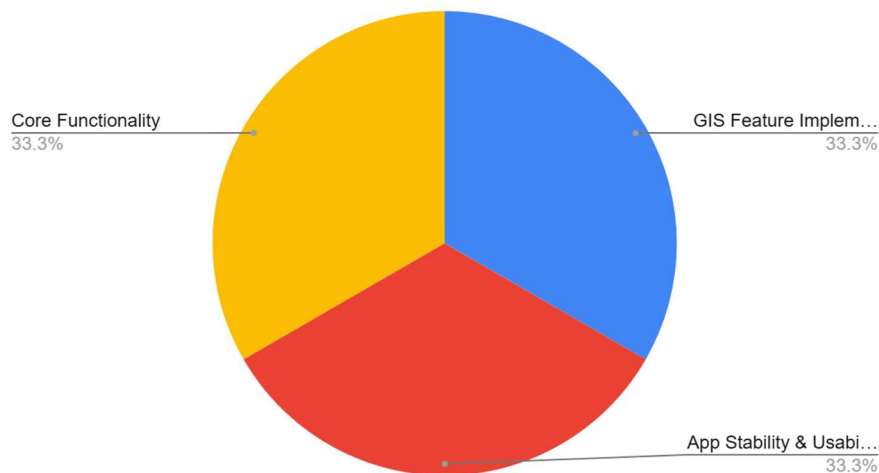


**Figure 11.** Distribution of per sub-them of the theme Indoor Positioning Systems (3 publications)

### 6. Location-Based (GIS) Systems

The systems combined outdoor mapping technologies such as GIS or GPS to show the places where items were discovered or last registered. The sub-themes addressed different points of system implementation: the development of GIS features like map markers and routing algorithms (Prashanth et al., 2025) (1 paper, 33.33%); the stability of the application and the design of the user interface (Hang & Shuangyun 2018) (1 paper, 33.33%); and the primary function of reporting and retrieving (Abraham et al., 2023) (1 paper, 33.33%).

### Location-Based (GIS) Systems

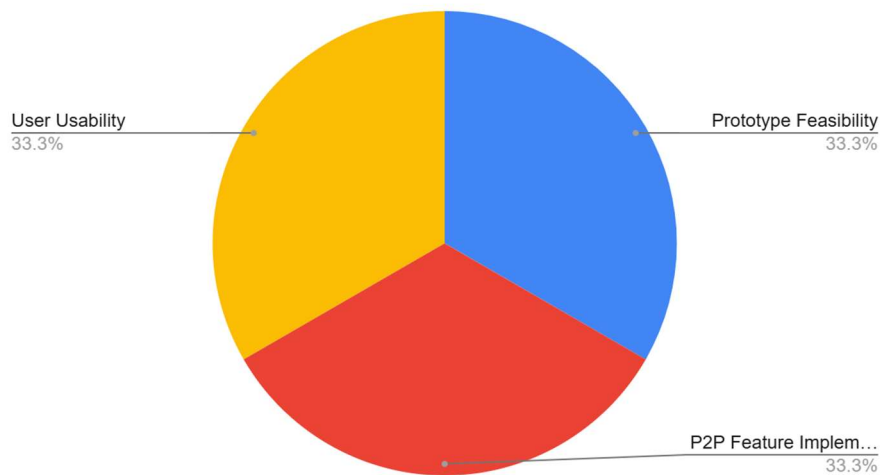


**Figure 12.** Distribution of per sub-them of the theme Location-Based (GIS) Systems (3 publications)

## 7. Community & Crowdsourcing

This category included systems that took advantage of collaborative user networks for finding lost items through community reporting or peer-to-peer methods. The outcomes were prototype feasibility evaluations (Choudhary et al., 2021) (1 paper, 33.33%), introduction of peer-to-peer features like messaging and notification systems (Dutta et al., 2024) (1 paper, 33.33%), and usability testing through participant feedback (Arbat et al., 2025) (1 paper, 33.33%).

## Communication &amp; Crowdsourcing

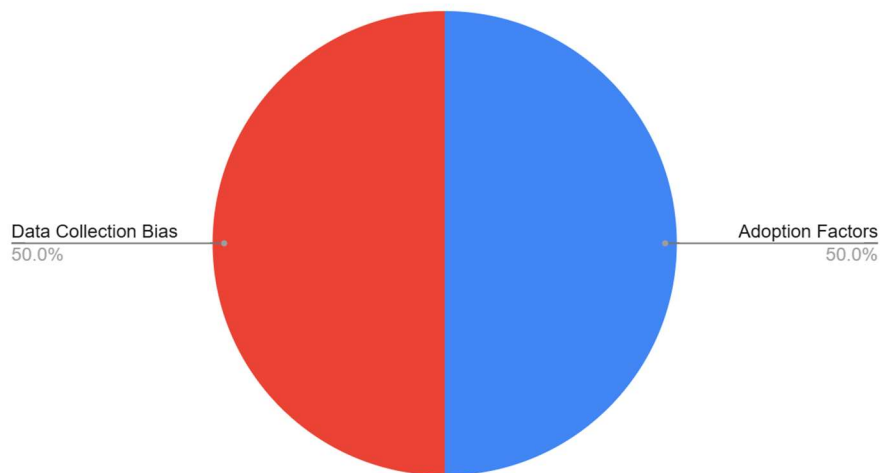


**Figure 13.** Distribution of per sub-them of the theme Community & Crowdsourcing (3 publications)

### 8. HCI & Methodology Studies

Unlike the others, these papers did not build a system. Instead, they studied how people interact with lost-and-found technologies. One paper focused on adoption factors (Koc et al., 2016) (1 paper, 50%), identifying psychological or social factors that influence whether users will adopt such apps. The other paper scrutinized the issue of data collection bias (Keusch et al., 2023) (1 paper, 50%) by stating that different demographics or devices could result in variations in data quality.

### HCI & Methodology Studies

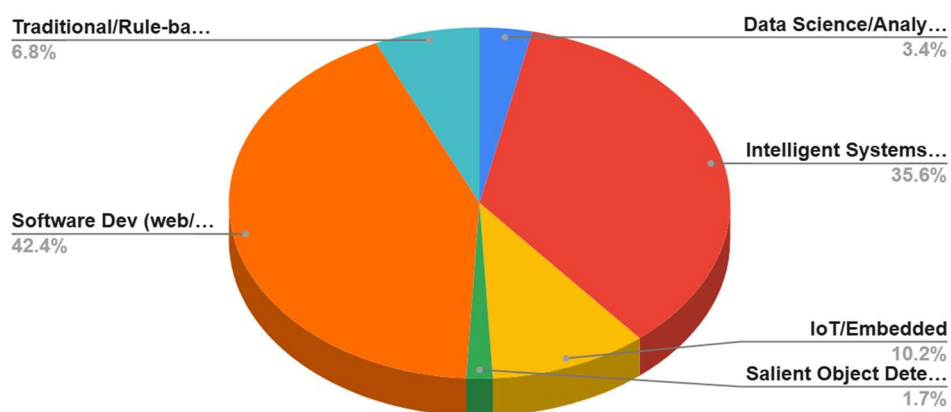


**Figure 14.** Distribution of per sub-them of the theme HCI & Methodology Studies (2 publications)

### 2.3.3. Methodological Analysis Results

#### 1. Method Category 1: Methodological Families

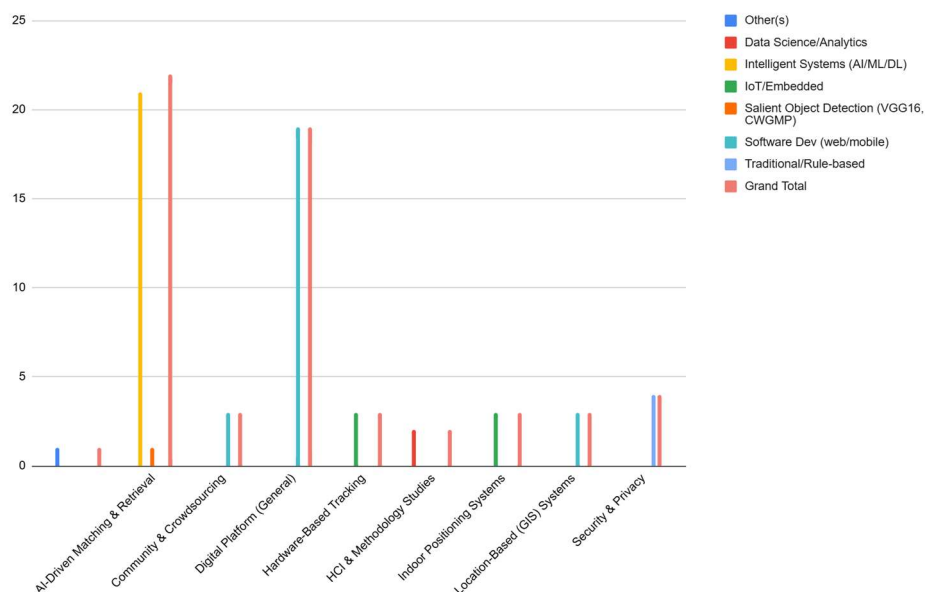
#### Method L1 Distribution



**Figure 15.** Distribution of methodological families (L1) across all studies (n=60).

When delving into the main family of methods (L1), the most common technique was Software Development (web/mobile), which 42.4% of the papers (25/60) (Abhiram et

al., 2024; Abraham et al., 2023; Alnaghaimshi et al., 2020; Arbat et al., 2025; Bataineh et al., 2015; Castro et al., 2022; Castro et al., 2022; Choudhary et al., 2021; Dhawal et al., 2025; Dutta et al., 2024; Hang & Shuangyun, 2018; Hossain et al., 2021; Krishna et al., 2025; Kumar et al., 2022; Muhammad-Bello et al., 2022; Pede et al., 2025; Prashanth et al., 2025; Romadhona et al., 2023; Salman & Athab, 2022; Shahzan & Arbaiy, 2025; Shrivastava et al., 2025; Sudhanshu et al., 2024; Tan & Chong, 2023; Tiwari et al., 2019; Vasavi et al., 2022) were devoted to. Intelligent Systems (AI/ML/DL) was very close with 35.6% (21/60) (Bruno, 2021; Dhanawardhana et al., 2025; Ghazal et al., 2015; Ghazal et al., 2016; Ghaleb et al., 2022; Jang & Kim, 2024; Karma & Darma, 2025; Khan et al., 2022; Konda, 2025; Liu et al., 2018; Ma et al., 2019; Meenalochini et al., 2018; Pang et al., 2018; Patil et al., 2024; Prawira & Saputri, 2024; Saemi et al., 2015; Sevakumar et al., 2021; Singla et al., 2023; Sivakumar et al., 2021; Yagi et al., 2022; Yao et al., 2019; Zhang & Hu, 2021; Zhou et al., 2021). The other methods had a much smaller presence: IoT/Embedded systems accounted for 10% (6/60) (Chen & Liu, 2019; Hamidi et al., 2023; Immaculate & Latha, 2017; Khruahong et al., 2018; Nadeem et al., 2021; Shoji & Ohno, 2022), Traditional/Rule-based logic was 6.8% (4/60) (Aiman et al., 2021; Sun et al., 2015; Xu et al., 2021; Zhang et al., 2020), and Data Science/Analytics was 3.4% (2/60) (Keusch et al., 2023; Koc et al., 2016).



**Figure 16.** Breakdown of methodological families (L1) by primary research theme.

The distribution of studies reveals clear methodological patterns across themes. The theme of AI-Driven Matching & Retrieval was mainly dominated by the usage of Intelligent Systems, with almost all the studies (21 out of 22) (Bruno, 2021; Dhanawardhana et al., 2025; Ghazal et al., 2015; Ghazal et al., 2016; Ghaleb et al., 2022; Jang & Kim, 2024; Karma & Darma, 2025; Khan et al., 2022; Konda, 2025; Liu et al., 2018; Ma et al., 2019; Meenalochini et al., 2018; Pang et al., 2018; Patil et al., 2024; Prawira & Saputri, 2024; Singla et al., 2023; Sivakumar et al., 2021; Sun et al., 2015; Yagi et al., 2022; Yao et al., 2019; Zhang & Hu, 2021; Zhang et al., 2020; Zhou et al., 2021) being conducted making use of AI, machine learning, or deep learning. On the opposite side, the Digital Platform (General) theme was almost entirely dependent on the standard web or mobile development, with around 95% (19 out of 20) (Abhiram et al., 2024; Alnaghaimshi et al., 2020; Bataineh et al., 2015; Castro et al., 2022; Castro et al., 2022; Dhawal et al., 2025; Hossain et al., 2021; Krishna et al., 2025; Kumar et al., 2022; Muhammad-Bello et al., 2022; Pede et al., 2025; Romadhona et al., 2023; Salman & Athab, 2022; Shahzan & Arbaiy, 2025; Shrivastava et al., 2025; Sudhanshu et al., 2024; Tan & Chong, 2023; Tiwari et al., 2019; Vasavi et al., 2022) of the studies opting for the traditional software development methods. Indoor Positioning Systems and Hardware-Based Tracking (Chen & Liu, 2019; Khruahong et al., 2018; Shoji & Ohno, 2022) mostly relied on IoT and embedded technologies, adopting sensor or hardware-driven strategies, while HCI & Methodology Studies (Keusch et al., 2023; Koç et al., 2016) pointed out the usage of data analytics and human-centered research, with concentrating on evaluations or methodological analysis instead of full system development. Just four studies (Aiman et al., 2021; Sun et al., 2015; Xu et al., 2021; Zhang et al., 2020), applied rule-based or traditional methods, pointing out that the older techniques are becoming less common gradually.

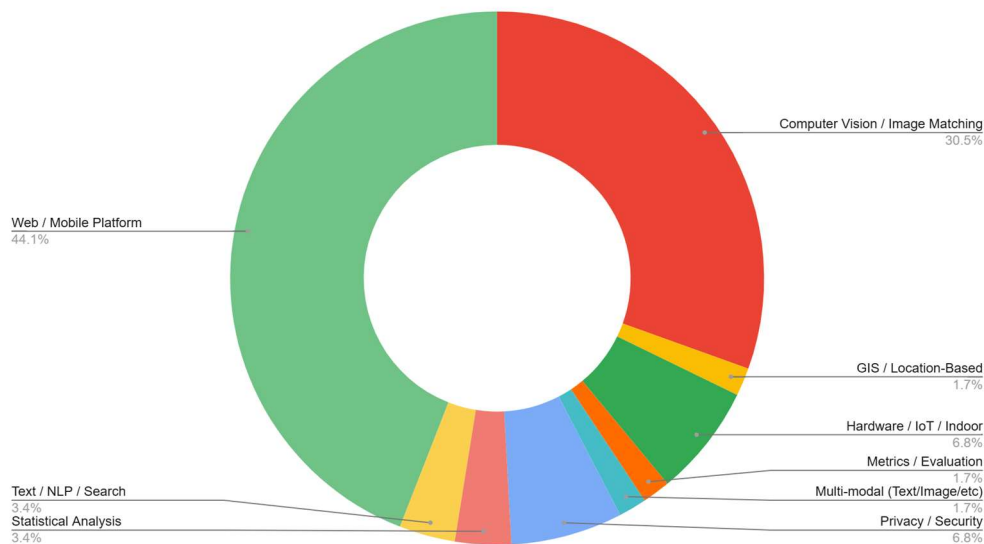
## 2. Method Category 2: Specific Technology Trends

Considering that very specific technologies (L2) were looked at, the pattern still stands. In Figure 8 it can be seen that the two biggest clusters are Web or Mobile Platform (26/60) (Abhiram et al., 2024; Abraham et al., 2023; Alnaghaimshi et al., 2020; Arbat et al., 2025; Bataineh et al., 2015; Castro et al., 2022; Castro et al., 2022; Choudhary et al., 2021; Dhawal et al., 2025; Dutta et al., 2024; Hang & Shuangyun, 2018; Hamidi

et al., 2023; Hossain et al., 2021; Immaculate & Latha, 2017; Krishna et al., 2025; Kumar et al., 2022; Muhammad-Bello et al., 2022; Pede et al., 2025; Romadhona et al., 2023; Salman & Athab, 2022; Shahzan & Arbaiy, 2025; Shrivastava et al., 2025; Sudhanshu et al., 2024; Tan & Chong, 2023; Tiwari et al., 2019; Vasavi et al., 2022) and Computer Vision or Image Matching (18/60) (Bruno, 2021; Ghaleb et al., 2022; Ghazal et al., 2015; Ghazal et al., 2016; Jang & Kim, 2024; Karma & Darma, 2025; Khan et al., 2022; Liu et al., 2018; Ma et al., 2019; Meenalochini et al., 2018; Patil et al., 2024; Prawira & Saputri, 2024; Singla et al., 2023; Sivakumar et al., 2021; Yagi et al., 2022; Yao et al., 2019; Zhang & Hu, 2021; Zhou et al., 2021). Research is mainly done in these two categories.

The chart highlights very clearly the areas that have been neglected and thus need attention among the critical ones. Just to illustrate, Privacy or Security received only 4 papers (Aiman et al., 2021; Sun et al., 2015; Xu et al., 2021; Zhang et al., 2020) (6.7%) attention while 2 (3.3%) worked on Text or NLP Search.

Method L2 (Top Techniques)

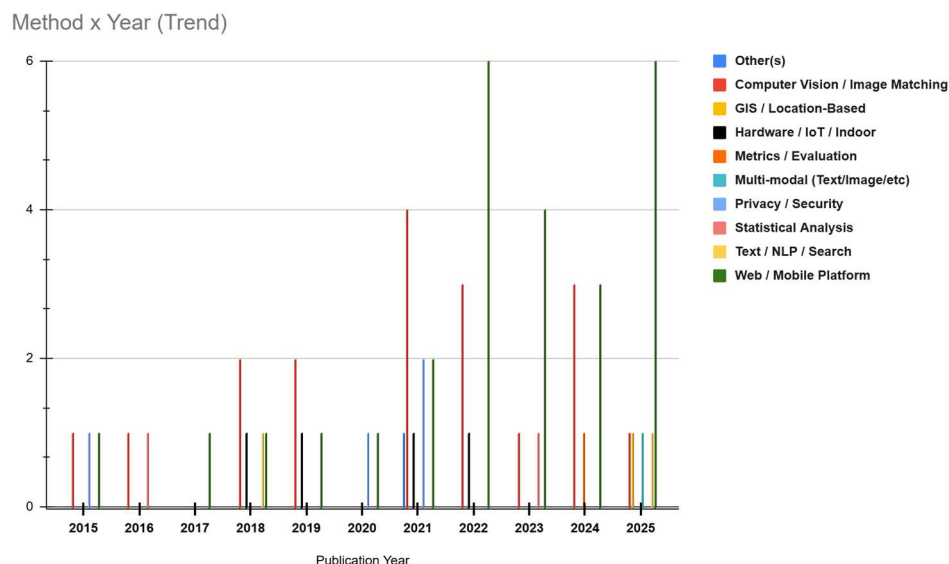


**Figure 17.** Frequency of specific technology groups (L2) used in the studies.

A visible trend of the methods by year of publication has been perfectly illustrated in Figure 9. The total number of papers published using the Computer Vision or Image Matching method is 18, out of which a remarkable 10 papers (two-thirds or 66.67%)

have been published since 2021. The recent peak of research activity in this theme is seen by notable years of 4 papers in 2021 and 2 in 2022 and 4 in 2024. This is in sharp contrast to the 2015-2020 period which saw a total of 6 such papers, with a maximum of only 2 each year.

This shows a clear change in the methodology used in the research area. The traditional Web or Mobile Platform development also increased (with 21 out of 26 papers published at the period 2021-2025), but the rise of computer vision as another major research area was the most important development. This indicates the abandonment of simple database-driven applications and the acceptance of the 'smart' systems that are capable to 'see' and recognize objects. The comparison between the other important research areas reveals how different the situation is: Privacy or Security (4 papers total), Text or NLP Search (2 papers total), and GIS or Location-Based (1 paper total) stayed low-frequency and did not experience any significant growth, thus, it is clear that the recent efforts have been primarily focused on CV and platform-building.



**Figure 18.** Trend of key technology groups (L2) by publication year.

### 3. Method Category 3: Evaluation Practices and Methodological Gaps

The most important finding of our research on methodology is that there is a major flaw in the evaluation of such systems. It was seen, and it is evident, that:

Only 22% (13/60) of studies used public benchmarks (like COCO, ImageNet, or Oxford 5k) to validate their AI models (Pang et al., 2018; Ma et al., 2019; Bruno, 2021; Ghaleb et al., 2022; Hassan et al., 2024).

Only 15% (9/60) conducted formal usability tests with actual users, for example, by using the System Usability Scale (SUS) (Bataineh et al., 2015; Muhammad-Bello et al., 2022; Hamidi et al., 2023; Romadhona et al., 2023).

Most papers just reported simple accuracy scores from their own private, small-scale datasets (Ghazal et al., 2015; Zhang & Hu, 2021; Zhou et al., 2021; Prawira & Saputri, 2024). This points to a major methodological gap: a lack of rigorous validation and real-world testing.

The gap has a strong connection to the scoping results. Areas such as Community & Crowdsourcing (Dutta et al., 2024; Choudhary et al., 2021) or Security & Privacy (Sun et al., 2015; Aiman et al., 2021) are still not explored as much as they should be, mainly because the methods have not been tested in these intricate, real-life situations. Proof-of-concept systems exist in abundance; however, very few have been actually approved for use. Future work should not only develop models but also involve ourselves in the tasks of integration, security, and user-oriented validation.

#### 2.3.4. Research Gap Analysis Results

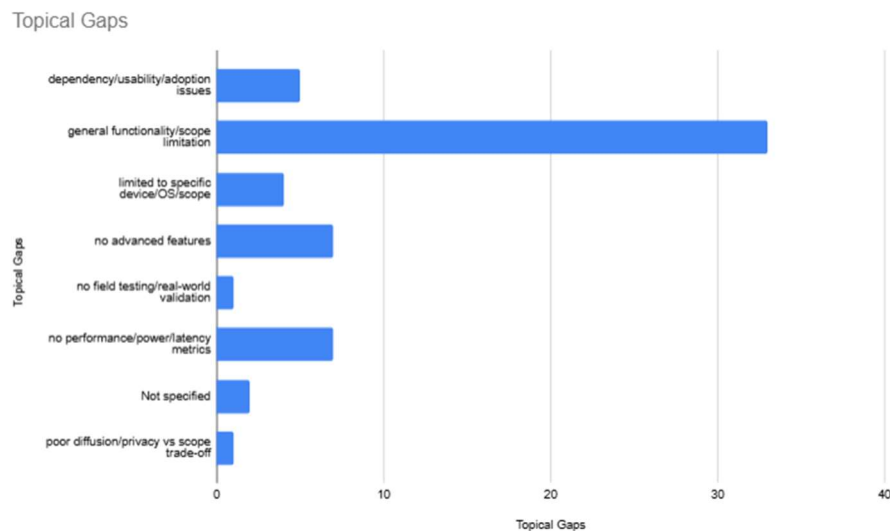
This section discusses the results of the research gap analysis, and classifies the gaps which are found in the reviewed studies. The authors of the analysis move through three principal groups of gaps: (1) Topical or Contextual Gaps, (2) Methodological Gaps, and (3) Result and Evaluation Gaps.

## 1. Topical Gaps

The analysis on the topical gaps showed that a part of the studies were demonstrating general functionalities or limitations of the scope, which was the most frequently identified problem appearing in thirty-three (33) studies (55%) (Abhiram et al., 2024; Alnaghaimshi et al., 2020; Bataineh et al., 2015; Bruno, 2021; Castro et al., 2022; Castro et al., 2022; Chen & Liu, 2019; Dhawal et al., 2025; Dutta et al., 2024; Hamidi et al., 2023; Immaculate & Latha, 2017; Jang & Kim, 2024; Khan et al., 2022; Khruahong et al., 2018; Krishna et al., 2025; Kumar et al., 2022; Karma & Darma, 2025; Liu et al., 2018; Ma et al., 2019; Meenalochini et al., 2018; Pang et al., 2018; Patil et al., 2024; Romadhona et al., 2023; Salman & Athab, 2022; Shoji & Ohno, 2022; Singla et al., 2023; Sivakumar et al., 2021; Sun et al., 2015; Tiwari et al., 2019; Yagi et al., 2022; Zhang & Hu, 2021; Zhang et al., 2020). This indicates that numerous lost and found systems do not have clear coverage or incorporation of the fundamental characteristics, and in many cases, the key parts that impact the total performance and the user experience are the ones that are missing. Seven (7) studies (11.7%) (Abraham et al., 2023; Arbat et al., 2025; Hossain et al., 2021; Muhammad-Bello et al., 2022; Pede et al., 2025; Shahzan & Arbaiy, 2025; Vasavi et al., 2022) were flagged as having no advanced functionalities and mainly depending on basic or old-time methods like keyword matching instead of being helped by image recognition, semantic analysis, or deep NLP models. Five (5) studies (8.3%) (Choudhary et al., 2021; Prashanth et al., 2025; Sudhanshu et al., 2024; Tan & Chong, 2023; Yao et al., 2019) indicate issues of dependency, usability, or adoption which leads to the disclosure that system efficiency was often a function of users' conduct or communication with the system being consistent.

Furthermore, four (4) studies (6.7%) (Ghazal et al., 2015; Keusch et al., 2023; Koç et al., 2016; Prawira & Saputri, 2024) were confined to certain devices, operating systems, or contextual scopes, therefore their implementations were hampered by being platform-dependent or geographically constrained. A few studies have exhibited other remarkable gaps: one (1) study (1.7%) (Ghazal et al., 2016) has no field testing or real-world validation, which implies that the evaluations were limited to controlled or simulated environments which could not be the case in complex, real-world environments. Another (1.7%) study did not include performance, power, or latency metrics. Moreover, one (1) study (1.7%) (Konda, 2025) talked about diffusion, privacy,

or scope trade-off concerns, where keeping user privacy limited system diffusion or large-scale data sharing, and two (2) studies (3.3%) (Aiman et al., 2021; Hang & Shuangyun, 2018) did not mention any specific gap.



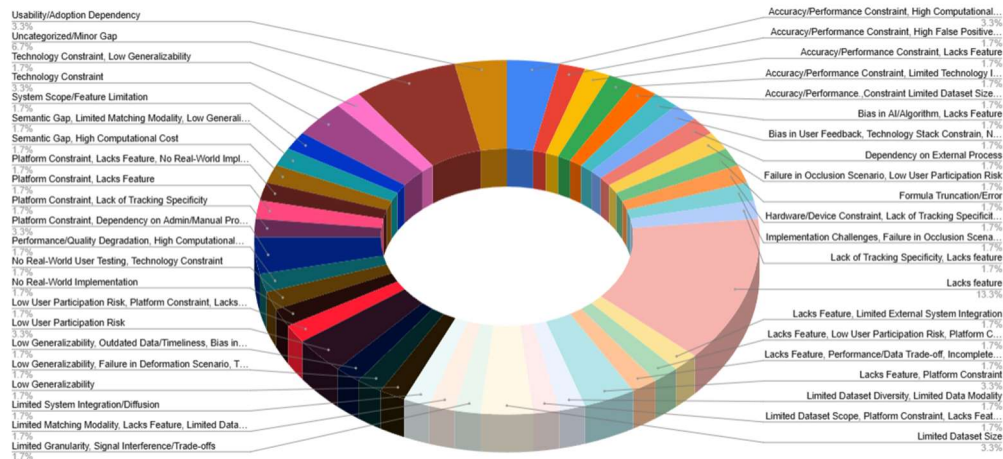
**Figure 19.** Topical Gaps Identified in Publications

## 2. Methodological Gaps

Out of sixty (60) studies reviewed, a number of methodological gaps were distinguished. The issues of accuracy and performance limitations were the most common, which were present in 9 studies, roughly 15% of the total studies. These gaps included limited optimization, high computational costs, and inaccuracies in model factors that together weaken the systems' robustness and reliability. Closely related were the cases of limited dataset size, scope, or diversity (6 studies, 10%).

Another gap was the lack of advanced system features and integration, observed in about 8 studies or 13% of the publications. Many studies employed basic functionalities or isolated frameworks without integrating external systems or complementary technologies. Similarly, a subset of works revealed low generalizability and technology or platform dependency, as well as hardware or computational constraints.

A final point from the studies is that some research suffers from the lack of real-world validation, relying only on simulations or controlled testing environments. Other minor but still important methodological drawbacks were such as bias in algorithmic design, limitations in optimization, and dependencies on usability or adoption.



**Figure 20:** Methodological Gaps Identified in Publications

**Table 5: Methodological Gaps Identified in Publications**

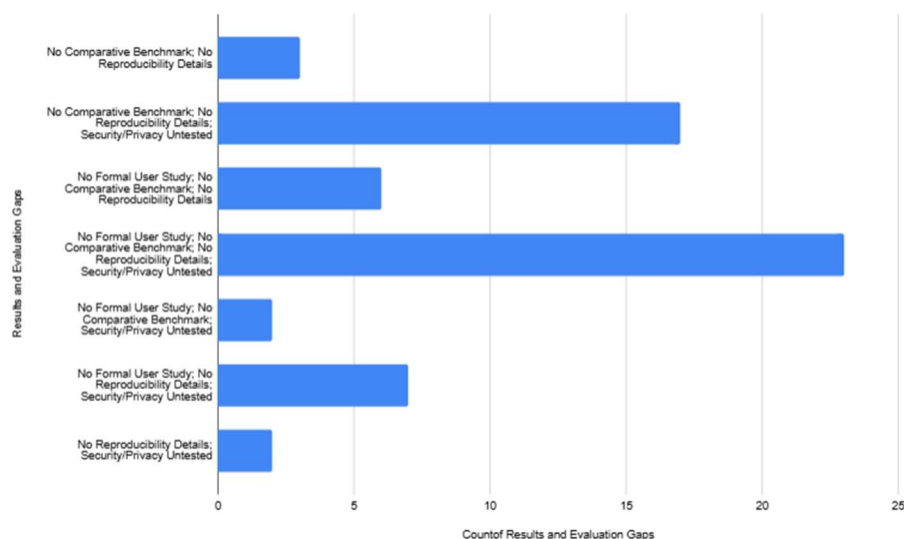
Methodological Gaps	COUNT of Methodological Gaps
Accuracy/Performance Constraint, High Computational Cost, Limited Dataset Size	2
Accuracy/Performance Constraint, High False Positive Rate, Low Success Rate	1
Accuracy/Performance Constraint, Lacks Feature	1
Accuracy/Performance Constraint, Limited Technology Integration, Dataset Dependency	1
Accuracy/Performance Constraint, Limited Dataset Size, Limited Dataset Scope	1
Bias in AI/Algorithm, Lacks Feature	1
Bias in User Feedback, Technology Stack Constraint, No Real-World Implementation	1
Dependency on External Process	1
Failure in Occlusion Scenario, Low User Participation Risk	1
Formula Truncation/Error	1
Hardware/Device Constraint, Lack of Tracking Specificity, Platform Scope Restriction	1
Implementation Challenges, Failure in Occlusion Scenario, Colorimetric Problems	1
Lack of Tracking Specificity, Lacks feature	1
Lacks feature	8
Lacks Feature, Limited External System Integration	1
Lacks Feature, Low User Participation Risk, Platform Constraint	1
Lacks Feature, Performance/Data Trade-off, Incomplete Data Security Implementation	1
Lacks Feature, Platform Constraint	2
Limited Dataset Diversity, Limited Data Modality	1
Limited Dataset Scope, Platform Constraint, Lacks Feature	1
Limited Dataset Size	2
Limited Granularity, Signal Interference/Trade-offs	1
Limited Matching Modality, Lacks Feature, Limited Dataset Size	1
Limited System Integration/Diffusion	1
Low Generalizability	1
Low Generalizability, Failure in Deformation Scenario, Technology/Parameter Dependency, Semantic Gap, High Computational Cost	1
Low Generalizability, Outdated Data/Timeliness, Bias in Self-Reported Data, Sampling Bias	1
Low User Participation Risk	2
Low User Participation Risk, Platform Constraint, Lacks Feature	1
No Real-World Implementation	1
No Real-World User Testing, Technology Constraint	1
Performance/Quality Degradation, High Computational Cost, No Real-time Optimization, Low Generalizability	1
Platform Constraint, Dependency on Admin/Manual Process, Lacks Feature	2
Platform Constraint, Lack of Tracking Specificity	1
Platform Constraint, Lacks Feature	1
Platform Constraint, Lacks Feature, No Real-World Implementation	1
Semantic Gap, High Computational Cost	1
Semantic Gap, Limited Matching Modality, Low Generalizability	1
System Scope/Feature Limitation	1
Technology Constraint	2
Technology Constraint, Low Generalizability	1
Uncategorized/Minor Gap	4
Usability/Adoption Dependency	2
<b>Grand Total</b>	<b>60</b>

### 3. Results & Evaluation Gaps

The third gap relates to gaps in results and evaluation. The analysis that was conducted on the sixty (60) studies that were reviewed brought to light that a good number of them, twenty-three (23, 38.3%) (Bruno, 2021; Chen & Liu, 2019; Dhawal et al., 2025; Dhanawardhana et al., 2025; Ghazal et al., 2015; Ghazal et al., 2016; Hang & Shuangyun, 2018; Hassan et al., 2024; Khan et al., 2022; Karma & Darma, 2025; Koç et al., 2016; Khruahong et al., 2018; Kumar et al., 2022; Liu et al., 2018; Ma et al., 2019; Meenalochini et al., 2018; Salman & Athab, 2022; Shoji & Ohno, 2022; Sivakumar et al., 2021; Singla et al., 2023; Tiwari et al., 2019; Yagi et al., 2022; Zhou et al., 2021), shows a variety of evaluation limitations, which included the lack of formal user studies, comparative benchmarks, and reproducibility details, in addition to untested security or privacy aspects. In the same vein, seventeen (17, 28.3%) (Arbat et al., 2025; Bataineh et al., 2015; Castro et al., 2022; Castro et al., 2022; Choudhary et al., 2021; Hamidi et al., 2023; Hossain et al., 2021; Jang & Kim, 2024; Keusch et al., 2023; Muhammad-Bello et al., 2022; Pang et al., 2018; Pede et al., 2025;

Prashanth et al., 2025; Prawira & Saputri, 2024; Sudhanshu et al., 2024; Yao et al., 2019; Hang & Shuangyun, 2018) studies do not have comparative benchmarking, reproducibility details and any kind of security or privacy validation. Moreover, there are six (6, 10%) (Abraham et al., 2023; Aiman et al., 2021; Nadeem et al., 2021; Patil et al., 2024; Sun et al., 2015; Xu et al., 2021) studies that do not provide comparative benchmarks or reproducibility details, whereas a smaller number of studies have reported other combinations of missing evaluations like incomplete security or privacy testing.

Thus, the findings reveal that the majority of the existing studies are characterized by weak or incomplete evaluation protocols. Also, the lack of reproducibility documentation together with comparative benchmarks restricts the assessment of models across them. See the figure below for a summary of the distribution of results and evaluation gaps that were identified in the reviewed studies.



**Figure 21: Results & Evaluation Gaps Identified in Publications**

## 2.4. Conclusion and Recommendations

The scoping review presented a clear increase in the research of mobile-based lost and found systems over the last ten years, most of the studies concentrated on either AI-driven matching (36.67%) or on general digital platforms (33.33%) development

during 2021 to 2025. The analysis revealed a fast-growing area consisting of 60 studies with the majority being from Asia (85%), especially India and China, covering the period from 2015 to 2025. These findings answer the main review objective, which is to map existing methods, architectures, and gaps in digital lost and found platforms by showing which technologies are most common and which parts of the system are still not well developed.

In relation to the current literature, the findings are mostly in line with the idea that many institutions and public spaces are already starting to move away from manual logbooks and simple keyword searching, and they are slowly shifting into smarter systems that rely more on modern technologies. At the same time, the review adds a more organized view by classifying eight main themes, such as AI-driven retrieval, digital platforms, hardware-based tracking, and community crowdsourcing, which helps connect scattered studies into one clearer picture. A key insight is that computer vision and image matching have become a very active area only in recent years, while topics like privacy, security, and HCI-focused evaluations are still relatively rare.

For practice and policy, the findings suggest that developers and institutions should not only build working apps but also consider stronger evaluation, privacy protection, and user-centered design when deploying lost and found systems. Universities, city offices, and other organizations may also use the list of methods and themes from this review as a basic guide when they decide if they should invest in AI matching features, GIS and location tracking, or just stick to simpler web or mobile systems that fit their needs and available resources.

However, the review also revealed several important gaps that future research needs to address. A lot of the studies relied on small or private datasets, had little to no usability testing, and were not tried in real-life settings, so it is still not very clear how well these systems really perform in everyday use. There is also limited work on community crowdsourcing models, advanced privacy-preserving techniques, and cross-platform or large-scale implementations, so more detailed reviews and experimental studies about these topics would be very useful.

Overall, this scoping review achieved its goal of mapping existing research on mobile-based lost and found systems using smart tagging and image recognition, detailing key themes, methodologies, and ongoing gaps across 60 studies. The results show that even if the field is growing and becoming more advanced, especially in AI and platform development, there is still a very strong need for more strict evaluation, better integration of privacy and security features, and designs that are really user-centered and aware of the actual context. These are areas that future researchers can still explore more deeply in their own studies

## 2.5. References

1. Hamidi, N. A., Aziz, A. A., Ismail, A., & Lokman, A. M. (2023). Found It! Object Tracker Mobile Application. Found It! Object Tracker Mobile Application, 1–6. <https://doi.org/10.1109/icraie59459.2023.10468161>
2. Prashanth, G. K., Kumar, U. U., Premasudha, B. G., Rajesh, N. L., & Vinothini, N. (2025). Mobile technology for efficient lost and found item retrieval using GIS based approach. Mobile Technology for Efficient Lost and Found Item Retrieval Using GIS Based Approach, 1–5. <https://doi.org/10.1109/icsses64899.2025.11009353>
3. Yao, Y., Zheng, X., & Ma, K. (2019). ILFS: Intelligent Lost and Found System using Multidimensional Matching Model. ILFS: Intelligent Lost and Found System Using Multidimensional Matching Model, 1205–1208. <https://doi.org/10.1109/smartworld-uic-atc-scalcom-iop-sci.2019.00224>
4. Sinha, S., Kaswan, S., Kumari, K., Kumar, A., Bisht, L., Katiyar, S., & Amita, N. (2024). A Novel Approach to Enhance Campus Lost and Found Services through Integration of QR Code with Personalized Item Registration. A Novel Approach to Enhance Campus Lost and Found Services Through Integration of QR Code With Personalized Item Registration, 1–7. <https://doi.org/10.1109/tqcebt59414.2024.10545109>
5. Tiwari, U., Mehruz, S., Sharma, S., & Pandey, V. T. (2019). Design of Python based lost and found website for college campus. 2019 International Conference on Power Electronics, Control and Automation (ICPECA), 1–5. <https://doi.org/10.1109/icpeca47973.2019.8975541>

6. Jang, S.-W., & Kim, J.-J. (2024). Lost Sharing Web Service Based on Image Classification Model. Harbin Gongcheng Daxue Xuebao/Journal of Harbin Engineering University, 45(11), 41–47. <https://harbinengineeringjournal.com/index.php/journal/article/view/3668>
7. Sultan, A., Hassan, M., Mansoor, K., & Ahmed, S. S. (2021). Securing IoT Enabled RFID Based Object Tracking Systems: A Symmetric Cryptography Based Authentication Protocol for Efficient Smart Object Tracking. Securing IoT Enabled RFID Based Object Tracking Systems: A Symmetric Cryptography Based Authentication Protocol for Efficient Smart Object Tracking, 7–12. <https://doi.org/10.1109/comtech52583.2021.9616967>
8. Romadhona, Y., Sjahrunnisa, A., & Yuhana, U. L. (2023). Lost and found: An application to search and find lost items. Kumpulan jurnal Ilmu Komputer (KLIK), 10(3), 290–305. <https://klik.ulm.ac.id/index.php/klik/article/download/566/pdf>
9. Khruahong, S., Kong, X., Sandrasegaran, K., & Liu, L. (2018). Develop An Indoor Space Ontology For Finding Lost Properties for Location-Based Service of Smart City. Develop an Indoor Space Ontology for Finding Lost Properties for Location-Based Service of Smart City, 54–59. <https://doi.org/10.1109/iscit.2018.8588014>
10. Zhao, H., & Peng, S. (2018). Design and Implementation of the Lost-and-Found System Based on Amap API. Design and Implementation of the Lost-and-Found System Based on Amap API, 1–4. <https://doi.org/10.1109/icsess.2018.8663776>
11. Castro, E., David, K., De Silva, K., Roxas, L., & Macaspac, J. (2023). AUFound: Retrieval of Misplaced Personal Belongings Through Mobile Application and Web-Based Management System Designed for Angeles University Foundation. AUFound: Retrieval of Misplaced Personal Belongings Through Mobile Application and Web-Based Management System Designed for Angeles University Foundation, 2229–2235. <https://doi.org/10.46254/an12.20220383>
12. Shoji, N., & Ohno, K. (2022). Position detection for lost items finding system using LoRa devices in large building. 2023 IEEE International Conference on Consumer Electronics (ICCE), 1–6. <https://doi.org/10.1109/icce53296.2022.9730134>

13. Immaculate, D. S., & Latha, P. (2017). Efficient detection of missing object using Zigbee technology. *Efficient Detection of Missing Object Using Zigbee Technology*, 8, 485–489. <https://doi.org/10.1109/ssps.2017.8071645>
14. Sun, J., Zhang, R., Jin, X., & Zhang, Y. (2015). SecureFind: Secure and Privacy-Preserving object finding via mobile crowdsourcing. *IEEE Transactions on Wireless Communications*, 15(3), 1716–1728. <https://doi.org/10.1109/twc.2015.2495291>
15. Chen, L., & Liu, J. (2019). EasyFind: A Mobile Crowdsourced Guiding System with Lost Item Finding Based on IoT Technologies. *EasyFind: A Mobile Crowdsourced Guiding System With Lost Item Finding Based on IoT Technologies*, 343–345. <https://doi.org/10.1109/percomw.2019.8730851>
16. Dutta, A., Tolani, Y., & Singhal, N. (2024). Automated lost and found system with peer-to-peer communication. *Journal of Emerging Technologies and Innovative Research (JETIR)*, 11(5), 132–138. <https://www.jetir.org/papers/JETIRGG06022.pdf>
17. Alnaghaimshi, N. I., Alenizy, R. A., Alfayez, G. S., & Almutairi, A. (2020). Mafqadat: Arabic Smartphone Application for Reporting Lost and Found Items. *Mafqadat: Arabic Smartphone Application for Reporting Lost and Found Items*, 1–4. <https://doi.org/10.1109/iccais48893.2020.9096791>
18. Dhawal, S. K., Barai, N. K., Jha, A. K., Prachi, A., & Ramchandani, S. M. (2025). LostLink - Lost anywhere find here. *International Journal of Innovative Research in Science Engineering and Technology (IJIRSET)*, 14(3), 3227–3232. <https://doi.org/10.15680/IJIRSET.2025.1403182>
19. Zhang, Y., & Hu, X. (2021). Object retrieval system based on feature matching technology. *2022 International Conference on Computer Engineering and Artificial Intelligence (ICCEAI)*, 158–161. <https://doi.org/10.1109/icceai52939.2021.00030>
20. Pang, S., Ma, J., Zhu, J., Xue, J., & Tian, Q. (2018). Improving object retrieval quality by integration of similarity propagation and query expansion. *IEEE Transactions on Multimedia*, 21(3), 760–770. <https://doi.org/10.1109/tmm.2018.2866230>
21. Tan, S. Y., & Chong, C. R. (2023). AN EFFECTIVE LOST AND FOUND SYSTEM IN UNIVERSITY CAMPUS. *Journal of Information System and*

- Technology Management, 8(32), 99–112.  
<https://doi.org/10.35631/jistm.832007>
22. Yagi, T., Nishiyasu, T., Kawasaki, K., Matsuki, M., & Sato, Y. (2021). GO-Finder: A registration-free wearable system for assisting users in finding lost objects via hand-held object discovery. In 26th International Conference on Intelligent User Interfaces (IUI '21) (pp. 139–149). ACM.  
<https://doi.org/10.1145/3397481.3450664>
  23. Krishna, V., Sai Karthik, K., Madupalli, K., Yasoda Rushitha, R., Chaitanya Murthy Komaravolu, S., & Suganya, P. (2025). WEB DEVELOPMENT VIT Lost and Found Design and Implementation of a VIT Lost and Found. ResearchGate. <https://doi.org/10.13140/RG.2.2.12362.27841>
  24. Bataineh, E. (2015). DESIGN, DEVELOPMENT AND USABILITY EVALUATION OF AN ONLINE WEB-BASED LOST AND FOUND SYSTEM. International Journal of Digital Information and Wireless Communications, 5(2), 75–81. <https://doi.org/10.17781/p001643>
  25. T, A., Eb, A. K., Km, M., Ap, V., & A, A. (2024). CampusTrace- Application for lost and found items on campus. Journal of Trends in Computer Science and Smart Technology, 6(2), 168–179. <https://doi.org/10.36548/jtcsst.2024.2.006>
  26. Koç, T., Turan, A. H., & Okursoy, A. (2016). Acceptance and usage of a mobile information system in higher education: An empirical study with structural equation modeling. The International Journal of Management Education, 14(3), 286–300. <https://doi.org/10.1016/j.ijme.2016.06.001>
  27. Dhanawardhana, B., Chalana, K., Abeywardena, I., Lankasena, N., & Paul, M. (2025). Enhancing Lost and Found Systems with Multi-Modal Deep Learning: Integrating SBERT and Siamese Networks for Improved Semantic Matching. Advances in Artificial Intelligence and Machine Learning, 05(02), 3736–3754.  
<https://doi.org/10.54364/aaiml.2025.52212>
  28. Meenalochini, M., Saranya, K., Rajkumar, G., & Mahto, A. (2018). Perceptual Hashing for Content Based image Retrieval. Perceptual Hashing for Content Based Image Retrieval, 2, 235–238.  
<https://doi.org/10.1109/cesys.2018.8723888>
  29. Zhang, Z., Zhou, F., Qin, S., Jia, Q., & Xu, Z. (2020). Privacy-Preserving image retrieval and sharing in social multimedia applications. IEEE Access, 8, 66828–66838. <https://doi.org/10.1109/access.2020.2984916>

30. Xu, J., Lin, Z., & Wu, J. (2021). Privacy-Preserving Task-Matching and Multiple-Submissions detection in crowdsourcing. *Sensors*, 21(9), 3036. <https://doi.org/10.3390/s21093036>
31. Patil, M. R., Patil, R. S., & Kushare, R. P. (2024). A Novel Approach "FOUNDIT" for Lost Items. *International Journal for Multidisciplinary Research (IJFMR)*, 6(1), 1–5. ID: IJFMR240112121
32. Sivakumar, M., Saravana Kumar, N. M., & Karthikeyan, N. (2022). An Efficient Deep Learning-based Content-based Image Retrieval Framework. *Computer Systems Science and Engineering*, 43(2), 683–700. <https://doi.org/10.32604/csse.2022.021459>
33. Chen, L., & Liu, J. (2019). EasyFind: Web-Based Lost and Found System. *MIT International Journal of Computer Science and Information Technology*, 11(1), 7–9. ISBN: 2230-7621
34. Bruno, A. (2021). An Automatic Image Content Retrieval Method for better Mobile Device Display User Experiences. *arXiv*. <https://doi.org/10.48550/arXiv.2108.12068>
35. Arbat, R., Rao, N., Vernekar, S., & Kokate, S. (2025). Traceit APP-ONE STOP DESTINATION FOR LOST/FOUND ITEM ISSUE. *International Journal on Science and Technology (IJSAT)*, 16(2), 1–10. ID: IJSAT25025250
36. Shrivastava, R., Owais, M., Zaid, M., Noman, M., & Maaz, M. (2025). Lost and Found Platform. *International Journal on Advanced Computer Theory and Engineering*, 14(1), 223–224. ISSN: 2319-2526
37. Abraham, T., Adarsh, P., Arya, A., Athul Babu, & Diya, S. (2023). Locating and retrieving lost objects using geolocation and real time communication. *International Journal of Creative Research Thoughts (IJCRT)*, 11(7), d303–d307. ID: IJCRT2307380
38. Singla, K., Singh, B., Kaur, K., & Choudhary, C. (2023). A Machine Learning Model for Content-Based Image Retrieval. In *2023 International Conference on Non-Conventional Energy, Computing and Security (NOCONST)* (pp. 1-4). IEEE. <https://doi.org/10.1109/NOCONST975.2023.10101215>
39. Salman, Z. A.-J., & Athab, O. A. (2022). Smartphone application for managing missed and found belongings. *MEST Journal*, 10(1), 66–71. <https://doi.org/10.12709/mest.10.10.01.08>

40. Castro, E., David, K., De Silva, K., Roxas, L., & Macaspac, J. (2022). AUFFound: Retrieval of Misplaced Personal Belongings Through Mobile Application and Web-Based Management System Designed for Angeles University Foundation. In Proceedings of the International Conference on Industrial Engineering and Operations Management (pp. 2229–2235). IEOM Society International. <https://doi.org/10.46254/an12.20220383>
41. Hassan, M. U., Zhao, X., Sarwar, R., Aljohani, N. R., & Hameed, I. A. (2023). SODRet: Instance retrieval using salient object detection for self-service shopping. Machine Learning With Applications, 15, 100523. <https://doi.org/10.1016/j.mlwa.2023.100523>
42. Keusch, F., Bähr, S., Haas, G., Kreuter, F., & Trappmann, M. (2020). Coverage error in data collection combining mobile surveys with passive measurement using apps: data from a German national survey. Sociological Methods & Research, 52(2), 841–878. <https://doi.org/10.1177/0049124120914924>
43. Muhammad-Bello, B. L., Lewu, O. P., Misra, S., Garg, A. K., Oluranti, J., & Maskeliunas, R. (2022). IReportNow: a Mobile-Based lost and stolen reporting system. In Lecture notes in electrical engineering (pp. 753–766). [https://doi.org/10.1007/978-981-16-8892-8\\_57](https://doi.org/10.1007/978-981-16-8892-8_57)
44. Ghazal, M., Haneefa, F., Ali, S., Alkhalil, Y., & Rashed, E. (2015). Mobile-Based Archival and Retrieval of Missing Objects Using Image Matching. 2015 3rd International Conference on Future Internet of Things and Cloud, 627–632. <https://doi.org/10.1109/ficloud.2015.80>
45. Al, M. G. E. (2016). Archival and Retrieval of Lost Objects using Multi-feature Image Matching in Mobile Applications. International Journal of Computing and Digital Systems, 5(1), 73–83. <https://doi.org/10.12785/ijcds/050107>
46. Zhou, M., Fung, I., Yang, L., Wan, N., Di, K., & Wang, T. (2024). LostNet: A smart way for lost and find. PLOS ONE, 19(10), Article e0310998. <https://doi.org/10.1371/journal.pone.0310998>
47. Pede, D., Ranawat, V., Shete, R., Gole, S., & Kolhe, T. (2025). Lost and Found Web Application. International Journal of Innovative Science and Research Technology (IJISRT), 1242–1244. <https://doi.org/10.38124/ijisrt/25may811>
48. Nadeem, A., Rizwan, K., Mehmood, A., Qadeer, N., Noor, F., & AlZahrani, A. (2021). A Smart City Application Design for Efficiently Tracking Missing Person in Large Gatherings in Madinah Using Emerging IoT Technologies. Mohammad

- Ali Jinnah University International Conference on Computing (MAJICC), 1–7.  
<https://doi.org/10.1109/majicc53071.2021.9526244>
49. Prawira, J., & Saputri, T. R. D. (2023). Lost item identification model development using similarity prediction method with CNN ResNet algorithm. *Journal of Autonomous Intelligence*, 7(2). <https://doi.org/10.32629/jai.v7i2.1381>
50. Hossain, M. J., Bari, M. A., Mahmud, M. T., & Khan, M. M. (2021). Web and Mobile Application Based Missing Query Platform (Lost and Found BD). 2021 IEEE 12th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON), 0074–0079.  
<https://doi.org/10.1109/iemcon53756.2021.9623081>
51. Choudhary, P., Choudhary, A. K., Srivastava, A. P., & Singh, A. (2021). Find Mine: Find the lost items via mobile app. 2021 2nd International Conference on Intelligent Engineering and Management (ICIEM), 491–495.  
<https://doi.org/10.1109/iciem51511.2021.9445379>
- a.
52. Khan, A. A., Shaikh, A. A., Shaikh, Z. A., Laghari, A. A., & Karim, S. (2022). IPM-Model: AI and metaheuristic-enabled face recognition using image partial matching for multimedia forensics investigation with genetic algorithm. *Multimedia Tools and Applications*, 81(17), 23533–23549.  
<https://doi.org/10.1007/s11042-022-12398-x>
53. Abraham, T., Adarsh, P., Arya, A., Athul Babu, & Diya, S. (2023). Locating and retrieving lost objects using geolocation and real time communication. *International Journal of Creative Research Thoughts (IJCRT)*, 11(7), d303–d307.  
<https://publisher.uthm.edu.my/periodicals/index.php/aitcs/article/view/16174>
54. Karma, I. G. M., & Darma, I. K. (2025). Application of feature-based image matching method as an object recognition method. *Bulletin of Electrical Engineering and Informatics*, 14(2), 1073–1079.  
<https://doi.org/10.11591/eei.v14i2.8803>
55. Ma, L., Jiang, W., Jie, Z., Jiang, Y., & Liu, W. (2019). Matching Image and Sentence with Multi-faceted Representations. *IEEE Transactions on Circuits and Systems for Video Technology*, 1.  
<https://doi.org/10.1109/tcsvt.2019.2916167>

56. Saemi, M. M., See, J., & Tan, S. (2015). Lost and Found: Identifying Objects in Long-term Surveillance Videos. In 2015 IEEE International Conference on Signal and Image Processing Applications (ICSIPA) (pp. 99–104). IEEE. <https://doi.org/10.1109/ICSIPA.2015.7412171>
57. Liu, Y., Xu, X., & Li, F. (2018). Image Feature Matching Based on Deep Learning. 2018 IEEE 4th International Conference on Computer and Communications (ICCC), 1752–1756. <https://doi.org/10.1109/compcomm.2018.8780936>
58. Konda, R. (2025). SMART TAGGING MEETS STRUCTURED CONTENT: REDEFINING METADATA FOR AI-POWERED ECOSYSTEMS. INTERNATIONAL JOURNAL OF INFORMATION TECHNOLOGY AND MANAGEMENT INFORMATION SYSTEMS, 16(2), 117–130. [https://doi.org/10.34218/ijitmis\\_16\\_02\\_009](https://doi.org/10.34218/ijitmis_16_02_009)
59. Ghaleb, M., Ebied, H., Shedeed, H., & Tolba, M. (2022). Image retrieval based on deep learning. Journal of System and Management Sciences. <https://doi.org/10.33168/jsms.2022.0226>
60. Vasavi, R. (2022). Lost and found system for VNR VJIET. International Journal of Engineering Research & Technology, 11(6), 277. <https://doi.org/10.17577/IJERTV11IS060277>