Operationalizing the Use of Sensor Data in Mobile Crowdsensing: A Systematic Review and Practical Guidelines

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Abstract. Smartphones have found their way into many domains because they can be used to measure phenomena of common interest. The Global Overview Report Digital 2022 states that two-thirds of the world's population uses a smartphone. This creates a power for measurements that many researchers would like to leverage. However, this in turn requires standardized approaches to collaborative data collection. Mobile crowdsensing (MCS) is a paradigm that pursues collaborative measurements with smartphones and the available sensor technology. Although literature on MCS has existed since 2006, there is still little work that has systematically studied existing systems. Especially when developing technical systems based on MCS, design decisions must be made that affect the subsequent operation. In this paper, we therefore conducted a PRISMA-based literature review on MCS, considering two aspects: First, we wanted to be able to better categorize existing systems, and second, we wanted to derive guidelines for developers that can support design decisions. Out of a total of 661 identified publications, we were able to include 117 papers in the analysis. Based on five main criteria (application area, goals, sensor utilization, time constraints, processing device), we show which goals the research area is currently pursuing and which approaches are being used to achieve these goals. Following this, we derive practical guidelines to support researchers and developers in making design decisions.

Keywords: Mobile crowdsensing · Mobile sensing · Systematic review

1 Introduction

Mobile crowdsensing (MCS) is a mobile sensing paradigm coined by Ganti et al. [19] where, on the one hand, the sensory capabilities of smartphones are exploited and, on the other hand, the crowd is placed in the foreground.

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This concept is promoted by the fact that two-thirds of the world's population own a smartphone [29], and is particularly suitable for measuring phenomena of common interest. MCS applications can be further distinguished between *participatory* [6] and *opportunistic sensing* [7] applications. Participatory sensing applications require active user involvement in the sensing process (e.g., the user has to actively trigger a sound measurement), while opportunistic sensing applications perform sensor measurements and data transmission automatically (e.g., the sound measurement happens in the background) [32]. MCS is used, for example, in the automotive [50] or medical [42] domain to capture large amounts of real-world data in a rather short time. However, the use of the paradigm is also accompanied by many challenges [31,34]. For example, data quality of the measurements must be ensured, incentives for contributing data must be provided, and the privacy of the users must be protected. The concept has existed for some time and can look back on more than 20 years of development [30]. However, it is still not widely used, and there are still too few studies [19] that systematically examine MCS and derive general development recommendations. In addition, such studies should be regularly updated and there are many pitfalls to consider. Therefore, this paper conducts a systematic literature review that addresses the following research questions (RQ):

- **RQ1**: What are the main goals of MCS applications?
- **RQ2**: Which sensors are MCS applications using to achieve these goals and how are they used?
- **RQ3**: What time constraints do MCS applications have?
- **RQ4**: On which processing device are MCS applications performing their computations (i.e., smartphone or server)?

Another goal of this literature review is to derive practical development guidelines that incorporate the aforementioned research questions. We conducted the analysis of the above research questions and the derivation of the guidelines based on the PRISMA guidelines [38]. 661 papers resulted from our search in the following databases used: ACM Digital Library, IEEE Xplore, PubMed, and Google Scholar. In the end, 117 papers could be included in the analysis. Despite the long history of the field of MCS, this shows that the number of papers presented should be considered rather small. In the following, we present the results of the review and show which general statements and practical guidelines can be derived to support MCS system design and development, for example, how the selection of the processing device can be systematically addressed.

The paper is organized as follows: In Sect. 2, related work is discussed. Material and methods are presented in Sect. 3, and the results are discussed in Sect. 4. Practical guidelines are derived in Sect. 5. The findings are discussed in 6, and the paper concludes in Sect. 7.

2 Related Work

Overall, there is an abundance of literature on MCS. As such, several general reviews and surveys related to MCS have already been conducted over the years.

In 2010, Lane et al. [32] present a survey on mobile phone sensing by reviewing existing applications and systems in this context. The authors describe the sensors available on smartphones at the time and discuss their capabilities. Furthermore, different application areas and sensing paradigms—including participatory and opportunistic sensing—are extracted and a general architectural framework is proposed. In their initial work on MCS in 2011, Ganti et al. [19] survey existing crowdsensing applications and classify them—similar to our work—into environmental, infrastructural, and social applications. Moreover, the authors discuss unique characteristics and respective research challenges of MCS applications. Similarly, in 2015, Guo et al. [23] review existing MCS applications and techniques along a number of categories. In addition, the authors highlight the unique characteristics of MCS applications and propose a conceptual framework based on the reviewed literature. Furthermore, the work considers MCS as human-in-the-loop systems and discusses the findings in terms of combining human and machine intelligence. More recently, in 2019, the survey of Liu et al. [34] aims to provide a comprehensive overview of recent advances in MCS research. The authors review the literature with respect to incentive mechanisms, security and privacy, resource optimization, data quality, and data analysis, with a particular focus on the data flow within MCS systems. Moreover, similar to our work, the findings and MCS applications are presented along four categories: indoor localization, urban sensing, environmental monitoring, and social management. Also, in 2019, Capponi et al. [8] present a comprehensive survey that considers MCS as a four-layered architecture consisting of an application, a data, a communication, and a sensing layer. In addition, the authors propose a number of taxonomies based on this architecture, classify existing MCS publications and systems according to these taxonomies, and discuss various conceptual and technical aspects of MCS systems. In addition to these more general and comprehensive reviews, there is also related work that focuses on specific aspects of MCS, such as incentives mechanisms [28,61], task allocation [52], data quality [25,33,46], resource limitations [53,54], security and privacy [13,25,41], or software architectures [35,57].

Overall, in the literature, either a rather general overview on MCS is provided or details on very specific aspects are discussed. However, there is a lack of practical guidance for researchers and system operators seeking to use MCS to achieve a specific goal, especially if they are new to this area of research. In this work, we aim to provide such guidance by reviewing the existing literature and identifying best practices for operationalizing MCS and the decisions to be made during system design. Furthermore, none of the above reviews include a review protocol that would make the review process transparent, traceable, and reproducible by other researchers. In particular, we were unable to find any reviews on MCS that use the PRISMA guidelines.

3 Materials and Methods

To produce transparent and reproducible results, we established a review protocol guided by the *Preferred Reporting Items for Systematic Reviews and Meta-Analyses* (PRISMA) statement. PRISMA is a collection of items designed to promote a transparent approach for systematic reviews and meta-analyses [38]. In the following, the defined eligibility criteria (see Sect. 3.1), the search strategy used (see Sect. 3.2), as well as the selection and data collection process (see Sect. 3.3) are described.

3.1 Eligibility Criteria

We established criteria that we used to decide on the eligibility of publications, i.e., whether a particular publication should be included or excluded. In this process, the following inclusion criteria (IC) were defined: **IC1:** The paper describes an MCS application; **IC2:** The paper describes a system using one or more mobile devices (e.g., smartphone or wearable) as sensors. In addition, we defined following exclusion criteria (EC) for the systematic review at hand: **EC1:** The system described in the paper does not use any mobile sensors; **EC2:** The paper does not describe how the data is sensed; **EC3:** The publication is older than 2007; **EC4:** The full text of the paper is not available or not available in English; **EC5:** The publication is not peer-reviewed. The search was limited to papers published from 2007 onwards. This year was chosen because it was the year Apple Inc. introduced its iPhone [14], which can be considered the beginning of the smartphone era [21].

3.2 Search Strategy

We used the scientific databases ACM Digital Library, IEEE Xplore, and PubMed as information sources for the review. In addition, a manual search via Google Scholar was performed. To identify relevant publications that met the eligibility criteria, the following search query was issued to the three databases on August 4, 2022:

```
Abstract:(crowdsens^*) AND (AllField:(application) OR
    AllField:(app))
```

Listing 1.1. Search query used for the databases.

As shown in Listing 1.1, the abstract or title had to contain a word beginning with *crowdsens* and somewhere in the paper the word *application* or *app* had to occur. In addition, a filter was applied limiting the search to only papers published from 2007 onwards to address exclusion criterion EC3.

3.3 Selection and Data Collection Process

The results of the queries to the chosen scientific database and the manual search were combined and duplicate records were removed. For the selection process, these papers were then screened based on their abstract and title to eliminate papers that are not relevant for this review. After screening, the full text of the remaining papers was examined, and further papers were excluded based on the defined inclusion and exclusion criteria. Furthermore, we extracted the following data from the included papers and used Microsoft Excel to record the results:

– Application area: Each paper is assigned to one of the four categories based on its application area (1) *urban sensing*, (2) *indoor localization*, (3) *environmental monitoring*, and (4) *social management, public safety, & healthcare*.
– Goals: The goals and subgoals pursued by the paper. Subgoals are smaller goals that the paper pursues (e.g., map matching or location matching), while goals are used as a broader term that encompasses multiple subgoals (e.g., localization). Each paper can be associated with any number of goals and subgoals.
– Sensor utilization: The sensors that are utilized by the MCS system and in what way or to achieve which of the identified goals and subgoals they are used (e.g., GPS used for localization or to measure the electron density in the atmosphere).
– Time constraint: The time constraints on the processing of the data (i.e., were the results needed in (near) real-time).
– Processing device: Which parts of the data processing were performed on which component of the system (e.g., smartphone or server).

4 Results

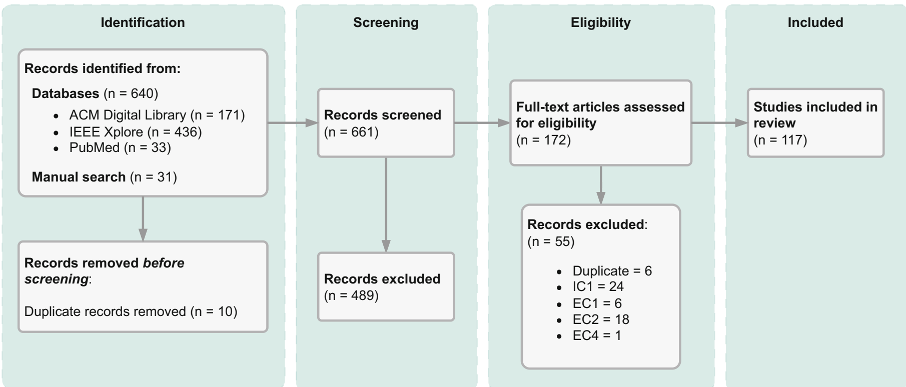

Fig. 1. PRISMA 2020 [38] flow diagram of the publication selection and screening process.

The publication selection and screening process is illustrated in Fig. 1. The database search returned a total of 640 publications. After adding 31 additional records through manual search and removing all duplicate results, 661 papers remained. The abstracts and titles of these publications were then screened, of which 489 papers were excluded. The full texts of the remaining 172 records were then assessed for eligibility and 55 records were excluded based on the defined inclusion and exclusion criteria. This process resulted in 117 publications included for the analysis at hand.

In the following, the results of the extracted data are presented. Note that for reasons of readability and space limitations, only a limited number of representative references are provided in the text for each category and aspect.

4.1 Application Areas

First, we analyzed the publications that were assigned to each category of application area. The number of publications per category is shown in Table 1.

Table 1. Number of publications per category ($n = 117$) and number of publications in each category that share a specific goal, in descending order by number of total occurrences. Each publication has been assigned to a single category, but may have multiple goals.

Category	UrbSens	IndLoc	EnvMon	SMPSH	All
Total	51 (44%)	16 (14%)	19 (16%)	31 (26%)	117 (100%)
Goal					
Localization	49 (96%)	16 (100%)	15 (79%)	22 (71%)	102 (87%)
Activity recognition	16 (31%)	4 (25%)	1 (5%)	6 (19%)	27 (23%)
Map generation	14 (27%)	7 (43%)	4 (21%)	1 (3%)	26 (22%)
Street observation	22 (43%)	0 (0%)	1 (5%)	0 (0%)	23 (20%)
Image analysis	9 (18%)	3 (19%)	6 (32%)	4 (13%)	22 (19%)
Sound analysis	5 (10%)	0 (0%)	3 (16%)	4 (13%)	12 (10%)
Data collection	2 (4%)	0 (0%)	3 (16%)	7 (23%)	11 (9%)
Air pollution	2 (4%)	0 (0%)	7 (37%)	0 (0%)	9 (8%)
Navigation	4 (8%)	2 (13%)	0 (0%)	1 (3%)	7 (6%)
Time estimation	6 (12%)	0 (0%)	0 (0%)	0 (0%)	6 (5%)
Nearby Bluetooth devices detection	0 (0%)	0 (0%)	1 (5%)	3 (10%)	4 (3%)
Crowd density estimation	2 (4%)	0 (0%)	1 (5%)	1 (3%)	4 (3%)

UrbSens: Urban Sensing, IndLoc: Indoor Localization, EnvMon: Environmental Monitoring, SMPSH: Social Management, Public Safety, and Healthcare.

The first category, urban sensing, is the largest application area (44%) and comprises technologies for sensing and acquiring data about physical areas and objects in urban spaces and the way people interact with them. This includes techniques to analyze the public infrastructure, such as roads [27,55], the WiFi density of a city [18], the waiting time for specific services [60,62], or other specific applications such as an online reposting system for fliers [22]. The second application area, indoor localization, comprises 14% of the included publications and focuses on localization techniques for indoor environments. This is a nontrivial problem, as conventional localization methods have many problems due to sensor inaccuracies within buildings, resulting in inaccurate data. Indoor localization techniques include localization on an indoor map [45,59], the reconstruction of indoor maps [11,59], or other applications such as generating a map of the WiFi coverage of a floor [44] and collecting fingerprints of a specific location [58]. The third application area, environmental monitoring, encompasses 16% of the publications. Environmental monitoring is conventionally implemented with wireless sensor networks (WSN). However, the installation and maintenance of WSNs are expensive, which is why MCS is often used to circumvent these costs. These applications include analyzing nightlife behavior of participants [48], detecting beautiful places in the city [36], or measuring electron counts in the ionosphere [40]. The last and second largest application area (26%) is social management, public safety, and healthcare. This category includes all applications that concern the physical and mental well-being of participants [26,43], as well as applications for disaster relief [49], disease detection [17], observation of large crowds [9,56], letting people report events they witness [37], or determining the relationship between two people [16].

4.2 Goals

Second, we analyzed the included publications in each category in terms of the goals they pursue and how these goals are achieved. The number of publications in each category that share a specific goal is shown in Table 1. Note that each publication may have multiple goals and corresponding subgoals.

For urban sensing, the most common goal is localization. In this context, map matching [27,39,55] matches the current position to a road on existing maps. In some cases, the number of possible routes can be restricted in order to have more options to reach this goal. One specific example case is route matching [62], where a list of possible routes is known. Another subgoal is simply to determine the position of the user, which is referred to as location matching [18,60]. This knowledge can, in turn, be used to extract features at a particular location [27], or to determine the time spent at a location [60]. Another prevalent goal in urban sensing is street observation. This goal includes application areas related to roads, such as inferring new roads [55], classifying intersections [27], detecting traffic anomalies [39], determining parking spaces [15], and monitoring road surfaces [2]. Activity recognition is another goal that can be used to reduce the amount of false data (i.e., sensing data at the wrong time) [5,62], sometimes aided by the use of sound recognition [62]. Activity recognition is often performed to help achieve other subgoals, such as road surface monitoring [2] or turn detection [10]. Another common goal is time estimation, which is often used to give an estimated time to enhance the user experience. This can be achieved in the form of predicting the arrival time, i.e., arrival time prediction [62], or the waiting time, i.e., waiting time prediction [5,60], of certain services to improve the user experience. Furthermore, many urban sensing applications aim to achieve map generation. These maps to be generated range from WiFi coverage maps [18] to cellular coverage maps [51], to maps highlighting road surface conditions [2], or free parking spaces on streets [15]. Other less common subgoals of urban sensing include photo quality determination [22], photo tagging [22], and photo grouping [22]. A common type of data collected is GPS traces, which are sometimes split to analyze the data for specific information [27,39].

Inherently, for indoor localization, the most prevalent goal is also localization. As the usage of GPS in indoor environments is highly error-prone, this goal is often achieved through the use of fingerprinting. With fingerprinting, the user's current location is determined by comparing the current sensor readings to previously recorded sensor readings with a corresponding location. This can be achieved either by WiFi fingerprinting [44,45], where a list of wireless access points (WAP) and their location is stored, or by magnetic fingerprinting [59], where the user needs to walk a bit to get the location, since the magnetic fingerprints a 3D vector and thus requires a temporal dimension. Another option to achieve this goal is tracking [20,44,45], using the accelerometer, gyroscope, and sometimes magnetometer to track the user's movement patterns. One of these tracking techniques is pedestrian dead reckoning (PDR) [44,45]. In PDR, the user's movement is tracked by knowing the starting location and estimating the distance and direction travelled. Since PDR makes estimates continuously, the estimation error accumulates over time, so a combination of PDR and another indoor localization technique has proven to be very beneficial. Furthermore, simple location matching [11] can also be used to detect the rough location in indoor environments. Map generation is another common goal of indoor localization. An application example is the reconstruction of a floor plan [11,20,59], which is implemented by using a PDR-similar approach [59], estimating the travelled distance and direction, or by letting participants record videos or photos of the environment [11,20]. These pictures are used for information extraction [11,20], picture concatenation [20], and connecting adjacent wall segments on photos to continuous boundaries to obtain hallway connectivity, orientation, and room sizes. Some MCS-applications also aim to map WiFi coverage of an indoor floor [44]. Other indoor localization subgoals are the navigation in an indoor environment [59], activity recognition [44,45], fingerprint collection [58], and QR code forgery detection [58].

Localization is also the most common goal in environmental monitoring, but most localization tasks in this area are fairly simple, such as location matching [4], as only the location of the user is needed for these applications, or detecting the location of a physical event (e.g., flowering cherries) [36]. Air pollution detection is one of the biggest challenges in environmental monitoring with MCS, as conventional smartphones usually lack the required sensors to address this problem. Therefore, most applications in this context use an external connected mobile sensor to measure the required data [4], but some applications attempt to detect air pollution by analyzing images captured by the mobile phone camera [24]. Image analysis is also used for other purposes, such as analyzing the brightness level of a video [48], analyzing the loudness level of a video [48], or simply extracting information from a picture [24,36] to detect a specific feature in the photos. Other subgoals of environmental monitoring include conducting a questionnaire [48], detecting points of interest [36], expanding areas of interest [36], and measuring electron counts in the ionosphere [40].

As in all other areas, localization is the most common goal for applications in the social management, public safety, and healthcare category. Location matching [16,26,37] is often required to simply determine the participant's current location. In some cases, an exact location is not required, but information about whether the participant is in a certain area is sufficient, which is referred to as geofencing [9]. Other event detection methods, such as swipe localization [37], where multiple participants indicate a direction in which an event is occurring, are also commonly performed. The second most frequent goal in this category is data collection [43,47]. This goal can be achieved through many different methods, such as conducting a questionnaire [43,47]. Other subgoals of this area include activity recognition [9,26], nearby people detection [16], relationship inference [16], determining swipe direction [37], detecting nearby Bluetooth devices [56], and crowd density estimation [56].

4.3 Sensor Utilization

Furthermore, we analyzed which sensors are used by the included applications and how they are used to achieve the goals and subgoals identified in Sect. 4.2.

The GPS sensor can be used for map matching [27,55] and location matching [11,60]. However, simply using GPS can lead to errors when the exact location is relevant, and therefore [60] proposed a possible solution by using the center of consecutive GPS readings. To measure electron counts in the ionosphere [40], dual-frequency GPS can be used. To do this, GPS signals are sent to the receiver at two different frequencies, and the delay between the arrival of these two signals can be used to calculate the electron count. Another option used for location matching is the usage of WiFi to detect WAP locations or to directly detect a specific WAP [5]. The WiFi sensor can also be used for WiFi density detection [18], route matching [62], which fingerprints cell tower IDs, and WiFi fingerprinting [44,45], where a list of WAPs is associated with a specific location and used for localization. GPS and WiFi can also be used together for location matching [16] or geofencing [9] to achieve even more accurate results. The magnetometer can be used for magnetic fingerprinting [59], which works much like the WiFi equivalent, with the only exception that a temporal dimension is required (i.e., the participant must walk the path for a while to determine the location). WiFi and the magnetometer can also be used in combination to produce a combined fingerprint for fingerprint collection [58].

Activity recognition is most often implemented by using the accelerometer [5,44,62]. This can be supported by utilizing the microphone for sound recognition [62]. Another way to use the accelerometer is to determine the tilt angle of the phone. This information can be used together with the magnetometer for swipe localization [37]. A variety of sensors can be used for movement tracking. Using solely the gyroscope, it is possible to detect whether the participant is making a turn [59]. Accelerometer and gyroscope can be used together to measure distances and orientation between start and finish [20]. Accelerometer, magnetometer and optionally gyroscope can be used together for PDR [44,45].

Other sensors used include the power sensor, the camera, the microphone, the Bluetooth sensor, and the ambient light sensor. The power sensor can be used, for example, to detect whether a phone is charging [27]. The camera can be used to take photos [20,22] and videos [11,36,48]. The microphone can record ambient sound [43], while Bluetooth can be used to detect nearby Bluetooth devices [56]. Finally, a combination of accelerometer, magnetometer and ambient light sensor can be used to determine photo quality [22].

4.4 Time Constraints

The time constraints per category of application areas are shown in Table 2. It can be seen that most applications either have no time constraints at all (51%), or only some of their components are time-relevant (27%). Only 21% of all considered publications state that their MCS application is completely real-time dependent.

Table 2. Number of publications with real-time constraints, without time constraint, and with a mixed approach. Per category of application areas and in total ($n = 117$).

Category	UrbSens	IndLoc	EnvMon	SMPSH	All
Total	$n = 51$	$n = 16$	$n = 19$	$n = 31$	$n = 117$
Real-time	10 (20%)	1 (6%)	4 (21%)	10 (32%)	25 (21%)
No time constraint	25 (49%)	10 (62%)	10 (53%)	15 (48%)	60 (51%)
Mixed	16 (31%)	5 (31%)	5 (26%)	6 (19%)	32 (27%)

UrbSens: Urban Sensing, IndLoc: Indoor Localization, EnvMon: Environmental Monitoring, SMPSH: Social Management, Public Safety, and Healthcare.

Most MCS applications do not have time constraints [20,27,48] because they are used to collect information that is not time-sensitive, for example, to update maps or obtain information only for eventual data analysis. As shown in Table 2, the highest percentage of application without time constraints can be found in the category of indoor localization, with many non-time-sensitive applications such as the reconstruction of indoor floor plans [11,20]. Other MCS applications aim to relay the gathered information to participants as quickly as possible, i.e., in real-time [26,36,62]. The highest proportion of applications with a real-time constraint is found in the area of social management, public safety, and healthcare. This category includes comparatively many time-sensitive applications such as healthcare monitoring [1], fall detection [26], disaster management during earthquakes [49], and crowd-management in mass gatherings [9]. Many MCS applications use a combination of real-time components and non-time-sensitive components [39,45,55]. The reason for the time constraints of these individual components is in most cases the same as mentioned above: a non-time-sensitive information is needed to further process the time-sensitive information. For example, the typical routing behavior of drivers is calculated without time constraint in order to detect traffic anomalies in real time [39].

4.5 Processing Device

In all the applications studied, data collection is always done via the smartphone or via external sensors connected to the phone. However, there are differences in the devices used to process the sensed data. The distribution of processing devices used per category of application areas is shown in Table 3.

Table 3. Number of publications that use local pre-processing or upload the data directly to a server where it is then processed. Per category of application areas and in total ($n = 117$).

Category	UrbSens	IndLoc	EnvMon	SMPSH	All
Total	$n = 51$	$n = 16$	$n = 19$	$n = 31$	$n = 117$
Local pre-processing	28 (55%)	7 (44%)	8 (42%)	15 (48%)	58 (50%)
Direct upload	23 (45%)	9 (56%)	11 (58%)	16 (52%)	59 (50%)

UrbSens: Urban Sensing, IndLoc: Indoor Localization, EnvMon: Environmental Monitoring, SMPSH: Social Management, Public Safety, and Healthcare.

Interestingly, about 50% of the analyzed MCS applications across all categories did not perform any local pre-processing before uploading the data to the server. This is often the case when the main purpose of the application is data collection [3], since no processing is required for this purpose, or when the application is not intended to interfere with the normal use of the phone and therefore does not require many computing resources [20,44]. The processing and computations performed by the server are usually more expensive calculations and include, for example, detecting traffic anomalies [39], arrival time prediction [62], waiting time prediction [5,60], or reconstructing a floor plan [11,20,59]. Many applications pre-process the data locally on the smartphone to reduce the amount of data to be uploaded and the burden on the participant devices [43,45,55]. In cases where avoiding data transfer is a higher priority than avoiding computations, these computations can be performed locally on the smartphone. These pre-processing and computation subgoals include route matching [62], splitting GPS traces [27,39], sound recognition [62], conducting questionnaires [43,48], recording ambient sound [43], determining swipe direction [37], and detecting nearby Bluetooth devices [56]. Finally, the processing of various subgoals is often executed either on the phone or the server. These include map matching [27,39,55], location matching [11,18,36], inferring new roads [55], extracting features at a given location [27], extracting information from a picture [11,20,36], intersection classification [27], activity recognition [5,26,45], fingerprinting [45,58,59], PDR [44,45], and geofencing [9]. In particular, activity recognition [5,44,45] is usually performed to verify the prerequisites for sensing data (e.g., the user is standing in a queue) and is therefore often performed locally on the smartphone.

5 Practical Guidelines

Based on the literature presented in the previous sections, best practices for operationalizing MCS are identified, including the decisions that must be made during the design and development of an MCS system. These decisions include the goals to be achieved by the system as well as the choice of sensors and the processing device to achieve these goals.

5.1 Goals, Subgoals, and Sensors

The first step in an MCS project is to consider what goals and subgoals the application should fulfill and how they should be achieved. Many goals require other goals or subgoals to achieve them. In addition, different sensors are required to achieve these goals and subgoals. Some common connections between goals, subgoals, and sensors are illustrated in Fig. 2 and are described in the following.

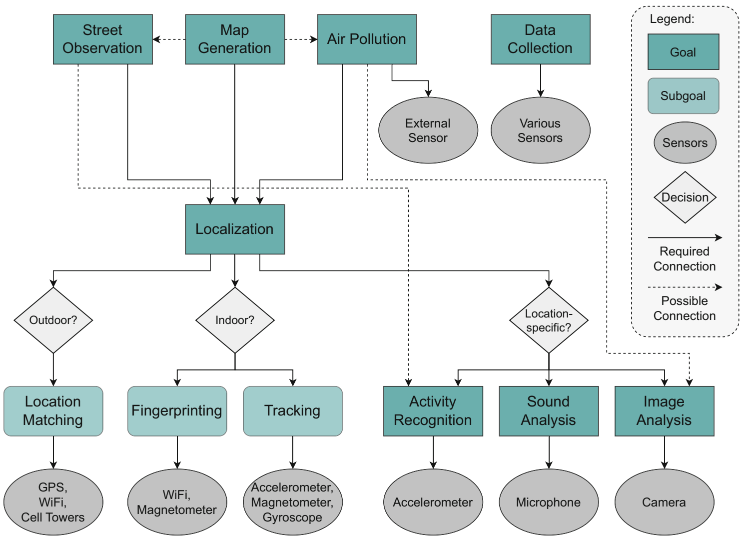

Fig. 2. Typical goals, subgoals, and sensors of MCS applications and their connections. Note that only common connections and not all possible connections are displayed.

If the location of the user is required for the application, localization must be performed. This goal can be achieved in different ways. The standard approach in large and open areas (e.g., a city) is location matching using GPS and, in some cases, WiFi or cell tower signals. If the application is intended to work in indoor environments, fingerprinting and tracking methods are preferable. In some cases, the user's location cannot be identified by coordinates, but by another concept, for example, if the user is on a train. This is a very application-specific problem, but the most commonly used techniques to address this problem are activity recognition (e.g., detecting the movement patterns of a particular vehicle) and sound analysis (e.g., detecting the sound of the IC card reader when boarding a bus [62]). Since street observation attempts to determine different road conditions, the participant's current location is always relevant for this purpose. Thus, some form of localization is always required, and depending on the specific subgoals (e.g., road surface monitoring), activity recognition is often additionally required to identify the specific road condition being monitored. Measuring air pollution with MCS can be performed only with smartphone-internal sensors using image analysis, but the more accurate solution is to use an external sensor connected to the smartphone (e.g., via Bluetooth). In this way, even more detailed information about air pollution can be collected, such as what types of substances pollute the air and to what extent. This measurement is usually always coupled with the location of the sensed air pollution, so in addition localization is required. Map generation also requires some form of localization to infer the coordinates of the objects or events being mapped. Typical applications are WiFi/cellular coverage maps of cities, maps containing information generated through street observation, air pollution, or reconstructing a floor plan. Activity recognition, image analysis, and sound analysis are most often used as utility functions to support another goal or subgoal of the application. Finally, if the main purpose of the application is data collection, the methods to achieve this goal depend on the data to be collected. For example, any combination of sensors can be recorded or a questionnaire can be conducted.

5.2 Processing Device

Another important consideration when designing an MCS application is the choice of the processing device. In other words, it must be decided whether the application will perform computations locally (i.e., on the smartphone) or on the server. This decision can be made for the entire application as a whole, but in most cases, it makes more sense to make this decision for each component of the application separately. The reason for this is that some components may have, for example, less security-relevant data or only some components have to deliver their results in real time. The most common aspects that are crucial for this decision are illustrated in Fig. 3 and explained in more detail in the following.

For each component of the MCS application, the first and probably most important aspect to consider is whether the component is intended to operate in (near) real time or whether it is not subject to any time constraints. If the results of the component are not time-sensitive, this aspect can be ignored. However, if the component is to evaluate and/or present the results to the user in (near) real time, the data must either be processed locally on the smartphone or a constant network connection is required (i.e., no opportunistic upload when connected to hotspots is possible). Most MCS applications are not time-sensitive or have only some time-sensitive parts, which means that only these parts of the application need special consideration when specifying the processing device. The second aspect to consider is whether it is feasible to run the components of the application locally at all. Components that only use the local data can easily run locally.

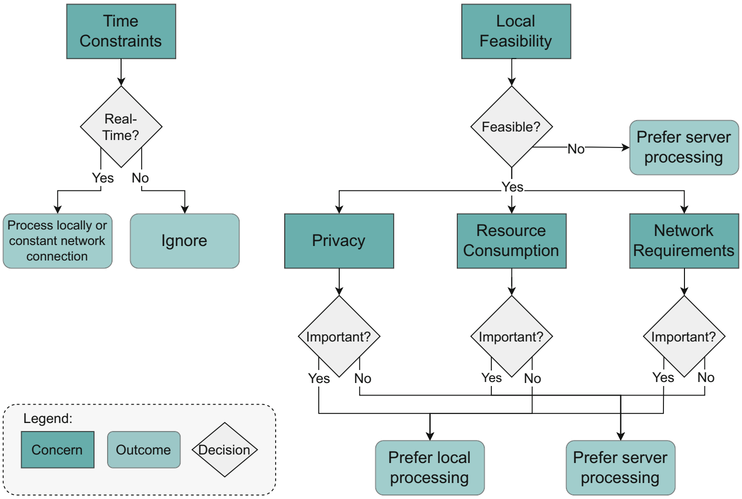

Fig. 3. Decision diagram for deciding on the processing device of a component of an MCS application.

However, components that require data from multiple devices/users (e.g., clustering GPS locations of multiple users) would need to download the remaining data from the server, while still uploading their own data for the other users to use. In most cases, it makes more sense to let the server perform this type of processing and download only the processing results from the server. If the local feasibility is generally given, privacy, resource consumption, and network requirements of the component should be considered. With respect to privacy, the more data a user uploads to the servers, the more privacy issues may arise. By performing as many computations as possible locally on the smartphone, the amount of potentially sensitive raw data uploaded can be reduced, thus avoiding privacy issues. For example, aggregations of raw data per time period can be performed directly on the smartphone, and only the aggregated data can be uploaded. Resource and power consumption are another aspect worth considering, also in terms of usability. Users will not be content with the application if the entire computational resources of their mobile device are occupied by the application and the battery life of their device is noticeably shortened by using the application. Since time-consuming computations can noticeably affect the battery life [12], it is preferable for such components to upload the data to the server and perform these computations there. Another aspect to consider is the network requirements. Due to the variable network coverage and mobility of users in MCS, a stable Internet connection cannot be guaranteed. In addition, most users will not have an unlimited amount of mobile network data. If the data should be able to be uploaded from anywhere possible, it is preferable to compress the data locally for further computations. For example, classification tasks where multiple data types are used as input and the result is only a class label can be performed locally to reduce the transferred data. Another option is to cache the collected data on the mobile device and opportunistically upload it when the device is connected to a WiFi hotspot. This approach circumvents the problem of mobile data usage and network connectivity for the participant, but does not allow real-time results.

6 Discussion

Overall, according to our analysis, urban sensing is the largest (44%) application area of MCS. The second largest area is social management, public safety, and healthcare (26%), followed by environmental monitoring (16%) and indoor localization (14%). In terms of the goals that MCS application pursue, localization is by far the most common (87%) goal. Activity recognition (23%), map generation (22%), street observation (20%), and image analysis (19%) are other commonly used goals in MCS. Depending on the specific application scenario, different sensors are used to achieve these goals. For example, GPS, WiFi, and cell towers are commonly used for outdoor localization, while WiFi, magnetometer, accelerometer, magnetometer, and gyroscope can be used for indoor localization. We propose that system designers of MCS applications explicitly define the goals and subgoals that the application should pursue and select the sensors and approaches that are best suited for these purposes and, in the optimal case, have been proven in the literature. The practical guidelines in Sect. 5.1 can be used to support this process. Only half (50%) of the analyzed MCS applications perform pre-processing locally on the mobile device (e.g., smartphone) before uploading the collected data to a server. We argue that for each component of the MCS application, separate consideration should be given to whether local pre-processing is feasible and reasonable, carefully balancing time constraints and resource consumption on the one hand, and privacy and network requirements on the other. This should be considered especially in light of the fact that most MCS applications have no time constraints (51%) or only some time-sensitive components (21%). However, some application scenarios, such as health monitoring and disaster management, are time-sensitive and therefore need to relay the collected information as quickly as possible, avoiding additional processing steps and prioritizing timeliness over resource consumption or network requirements. The decision diagram in Sect. 5.2 can be used to support the decision on the processing device for a particular component of an MCS application.

7 Conclusion

Mobile crowdsensing is a strategy that capitalizes on the current capabilities and prevalence of smartphones. From a technical point of view, many challenges have been identified and solutions presented that are promising so far. For example, incentive mechanisms and data quality are identified as challenges in the literature. Although the research field is not young, there are still too few fundamental considerations (e.g., in the form of literature reviews) or guidelines on how MCS systems can be designed. Therefore, using the existing literature, we examined what the goals of current approaches are, how these goals are achieved, and what guidelines for developers and researchers can be derived based on the widely used PRISMA guidelines. We have shown that localization is the most important goal of current approaches, followed by activity recognition and map generation. Nevertheless, we see the opportunities, for example in healthcare, much broader than MCS is operationalized so far. Despite the very focused goals currently being pursued with MCS, we were able to gain new insights for the work at hand based on the defined research questions. On the one hand, we were able to derive technical results, such as guidelines for decisions on sensors, processing devices, and time constraints. On the other hand, it should be noted that this systematic literature review using major academic databases resulted in only 117 papers that provided enough technical details to be included, despite the long history since the introduction of the technology. The presumption is, and the COVID-19 pandemic has made it clear, that we need the wisdom of the crowd. Technical operationalization certainly lags behind the opportunities, as the present study shows. With the extracted practical guidelines, we hope to have taken another step towards dissemination of MCS and its potential.

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