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A Survey on Mobile Crowd-Sensing and Its Applications in the IoT Era

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ABSTRACT Mobile crowd-sensing (MCS) is a new sensing paradigm that takes advantage of the extensive use of mobile phones that collect data efficiently and enable several significant applications. MCS paves the way to explore new monitoring applications in different fields such as social networks, lifestyle, healthcare, green applications, and intelligent transportation systems. Hence, MCS applications make use of sensing and wireless communication capabilities provided by billions of smart mobile devices, e.g., Android and iOS-based mobile devices. The aim of this paper is to identify and explore the new paradigm of MCS that is using smartphone for capturing and sharing the sensed data between many nodes. We discuss the main components of the infrastructure required to support the proposed framework. The existing and potential applications leveraging MCS are laid out. Furthermore, this paper discusses the current challenges facing the collection methodologies of the participants' data in task management. The recent issues in the MCS findings are reviewed as well as the opportunities and challenges in sensing methods are analyzed. Finally, open research issues and future challenges facing MCS are highlighted.

INDEX TERMS Mobile crowd-sensing, smartphone, data sensor management, Internet of Things, location privacy.

I. INTRODUCTION

Smart phones are ubiquitous mobile devices expected to proliferate rapidly, and their penetration is estimated to be in the order of billions worldwide. Delivery applications such as mobile application stores (Apple AppStore, Google Play Store, etc.) and social media have transformed mobile phones into intelligent computing devices using the instant download of applications [1]. Smartphone vendors are continuously increasing the number of built-in sensors, a fact that makes them an excellent contextual information provider. Thus, smartphones can be used for large scale sensing of the physical world at low cost by leveraging the available sensors on the phones. With the proliferation of smartphones, several sensing approaches have emerged such as mobile phone sensing [2]. To enhance the user experience, many of the applications that come installed or can be downloaded from the online application delivery platforms take advantage of sensors available on the phone. The fixed sensors on the smartphone offer the chance to develop innovative applications in many sectors such as environmental monitoring, healthcare, and transportation [3]. In such applications, smartphones play the role of base sensor nodes and gateways depending on the availability of the mobile phones within a region of interest. Similarly, sensors deployed in today's smartphones are witnessing a continuous improvement of their hardware and software capabilities Smartphones can gather process and transfer data between users. Eventually, smartphones, similar to static nodes are capable of sensing, computing, and communicating [4], [5]. However, the main difference is that smartphones are moving and repositioning themselves in the network all the time. In such innovative sensory networks, smartphones can collaborate with traditional sensor nodes to form a global-scale network formed by billions of sensor nodes that are dynamically deployed, to support the needs of a variety of applications and services. The embedded sensors in mobile phones are leveraged for various sensing tasks for MCS applications of particular interest [6].

MCS takes advantage of large number of smartphone devices to collect data efficiently enabling several significant applications [1]. MCS refers to the use of smartphones owned by a diversity of participants to gather and share data of incidents of common interest. The basic idea of MCS is trying to consolidate the sensing idea with a ''collective'' sensing view The sensed data collected using fixed sensors in traditional sensing techniques is substituted by data collected from citizen-generated content within social media or applications using smartphones [7], [8]. This creates a great amount of information, which complements sensor data with the opinions and experiences of citizens [9].

MCS allows a large number of smartphones to be used for activities that have a large public impact and the exchange of information between their users and can be supported by the cloud. With the support of the cloud, data fusion techniques can be applied on the information collected from the smartphones. This allows mobile sensing to be a multipurpose platform that can replace static sensing infrastructure to support a comprehensive range of applications from smart city applications and safety to monitoring the environment [10]. An emerging sensing paradigm is mobile crowd-sensing [13] which comes in a variety of modes: (i) opportunistic sensing [11], [12], (ii) participatory sensing [11], and (iii) people/human-centric sensing [11], [14], [15]. The traditional sensor network supports a single use case, while crowd-sensing data may contribute to various use cases [16].

Mobile sensing devices are extensively available and are a rich and inexpensive source of sensing data. Recently, varieties of sensors exist in most smartphones for different purpose. iPhone users represent 59.6 million in one database with embedded sensors including GPS, accelerometer, gyroscope, ambient light, proximity, microphone, and camera sensors. Light sensors are used for fine-tuning the screen brightness. Both proximity and light sensors permit the phone to complete simple forms of context recognition linked with the user interface. The GPS allows the phone to localize itself and enables regional or location aware searches, navigation, and mobile social networking applications [17], [18]. Both compasses and gyroscopes determine direction and orientation, improving location based applications depending on the GPS [19]. The accelerometer has a different role, it can be used to identify several activities such as running, walking, and standing. The most powerful sensors found in any smartphone today are the camera and microphone, which are possibly the most global sensors on the planet [20]. The camera on the front of the phone can also be used for conventional tasks such as tracing the user's eye movement as an intermediary to start applications [21], [22]. In addition to traditional purposes for the aforementioned sensors, more advanced applications are developed to further utilize the sensors. The mode of transportation of a user can be detected by a combination of accelerometer data and location from the GPS sensor This combination of sensor readings allows us to detect if the user is riding a bike, a car, a bus or even walking or running [23]. The sensors allow new applications in a wide diversity of domains, such as healthcare that uses accelerometer to measure the user's activities [24]; safety and environmental monitoring which uses GPS for location data collection [25]; transportation which also uses GPS [17], [26]; social networks based on Wi-Fi and GPS [17] These can open new areas of research called mobile phone sensing. The MCS research is focused on the possibility of growing pervasive urban and individual mobile technologies to support citizen daily life. The evolution of mobile phones has often been paired with the introduction of new sensors. For example, accelerometers have become more popular after being utilized to enhance photos captured by the camera and after using it in graphical user interface [19]. Sensors are used to automatically determine the orientation of the mobile phone screen and use that information to mechanically switch the display between landscape and portrait or properly orient the photos taken.

Mobile crowd-sensing can be considered as crowdsourcing where the resource provided by the crowd is their sensing capabilities. Crowdsourcing is a group of outsourcing techniques that utilizes independent, volunteer, and paid human resources to complete a specific task [27]. It is also a process in which a task, a project, or a problem is performed by a group of private and geographically isolated participants. The participating members are compensated or provided with recognition once the problem is solved or the task is completed. Smartphone-based crowd-sensing take advantage of the tremendous growth in network-monitoring applications. Several smartphone based crowdsourcing applications use the call data records (CDR). The CDRs of social network refers to the information on communications between a large number of people at a certain time, which contains actual observations of communications between people and is stored by all telecom operators, though data semantics vary slightly among them [28]. Faggiani *et al.* [29] discuss the most important opportunities offered by crowdsourcing and the associated key challenges. Portolan, a smartphone-based crowdsourcing system, has been built to demonstrate possible benefits of crowdsourcing. For a large number of clients, the Portolan server is used to coordinate the activities of data collection. Portolan is able to build signal coverage maps and produce a graph of the Internet at the autonomous system (AS) level. Furthermore, Ren *et al.* [27] focus on the use of crowdsourcing for data collection to address numerous solid challenges in widespread computing systems such as participatory urbanism that encourages new methods and approaches for individual citizens to become active participants within their city, neighborhood, and urban self-reflexivity. Another example is the use of mobile phones as environmental sensing platforms that support community action to enforce positive societal change. Rosen *et al.* [30] proposed a Mobile Crowdsourcing Network for wireless network management (MCNet). This tool permits users to implement crowdsourcing of WiFi performance measurements. Wi-Fi was used to communicate between mobile devices such as smartphones or tablets and many access points that are fixed in a university or organization setting. Few hundred users used the MCNet application tool, where at a certain time at least 20 mobile devices should be connected to the network to guarantee an efficient crowdsourcing of measurements. They deployed this tool in one corporate and one university WLAN. They worked together with the network IT engineer to enhance the latency and throughput to as high as 37% and 38%, respectively. Their results showed that MCNet is an effective, practical system for crowdsourced Wi-Fi performance measurements in large and complex WLANs.

A. POSITIONING THE PROVIDED SURVEY

There are several surveys in the litreture that address the broad topic of mobile crowd-sensing. The survey in [1] focuses on existing work on mobile crowd-sensing strategies with emphasis on reducing the resource cost and achieving high Quality-of-Service, however it did not address sensing techniques and applications. Lane *et al.* [19] give an overview of the sensors on the phone and their potential uses The paper targets novice or practitionars new to the field of MCS. Finally, the survey in [5] addresses the use of mobile phones in detecting movements and actions. To the best of our knowledge, all the reviewed surveys did not consider the most common mobile crowd application modes such as participatory and opportunistic modes that are used in most of the mobile crowd-sensing applications. In this work, we address mobile crowd-sensing applications focusing on the participatory and opportunistic modes. The detailed objectives of our contribution are listed below:

1) Present a comprehensive literature review of mobile crowdsensing, demonstrating the shift from traditional sensing paradigm towards MCS paradigm, and introducing several research work done in this field using smartphone sensors.
2) Describe the current techniques and frameworks for MCS.
3) Discuss the significant research findings of MCS and identify the application areas considering both the two urban sensing namely participatory and opportunistic sensing
4) Explore applications of crowdsensing in areas such as healthcare, environment, smart city, infrastructure, social networking, tourism, Sports and public safety and military applications (as shown in Figure 1).
5) Discuss the challenges and explore new research areas in MCS deployment such as enhancing the collected data accuracy.

We believe this work can open doors to more research on this vital topic inspiring designers to develop attractive mobile crowd-sensing systems while considering privacy of the participants before system deployment.

The remainder of this paper is structured as follows: Section 2 contains the MCS paradigm and overview. Section 3 describes the MCS framework with its components such as data collection; communication media; data aggregation; and data storage and classification. MCS applications including healthcare, environmental, smart city, infrastructure social networking, tourism, sports and public safety and military applications; are described in Section 4. A discussion of extensive investigations of MCS is presented with open research issues and challenges are described in Section 5, and finally, the paper concludes in Section 6.

II. MCS APPLICATION MODES AND PARTICIPANT SELECTION

Human participation in MCS varies depending on the application mode. There are two application modes of sensing data collection which are active (participatory) and passive (opportunistic) [15].

A. APPLICATION MODES

The participatory (active sensing mode) depends on the participants in performing some actions. In this method, the participant willingly takes the responsibility of entering the information. The active mode requires the user's participation and even the user's involvement in the operation [31]. For example, incident reporting requires the user to move to the incident's location, to take videos and photos, and finally send them to the monitoring center.

The opportunistic (passive sensing mode) depends on a set of applications installed on the users smartphones performing a set of predefined actions. In this way, the application gathers data without notifying the user. This method should meet the application requirements and automatic data collection, such as collecting a user's geolocation information [8], [32]. In the passive participant mode, the MCS applications do not require any involvement from the user of the mobile device except downloading the mobile application and allowing his/her mobile device to cooperate and participate in the MCS operation [31]. For instance, an application that monitors the environment in an urban area can rely solely on smartphones for data collection without the user's involvement. Figure 2 shows a comparison between the steps involved in participatory and opportunistic sensing.

Jayaraman *et al.* [33] presented the Mobile Sensor Data EngiNe (MOSDEN) as a collaborative mobile crowd-sensing framework to develop and deploy opportunistic sensing applications. The framework was used for an environmental

FIGURE 1. MCS application areas.

monitoring scenario (e.g. noise pollution) in smart cities. The framework scenario has three steps. Initially the remote-server registers for the required data to be collected from the concerned users. Then, the smartphones collect the data using their embedded sensors, preprocess the data and send it to the remote-server. Finally, the crowd-sensing applications gets the data from the remote-server for further processing and visualization. The authors implemented and evaluated the framework performance on an Android-based mobile to validate the possibility and efficiency of running collaboratively in mobile opportunistic sensing applications. They mentioned that MOSDEN performs well under load in collaborative environment.

B. PARTICIPANT SELECTION

To perfectly select the participants in mobile crowd-sensing paradigm, several points need to be covered such as participant location, participant privacy, participant incentive, and participant connectivity Nowadays, a huge amount of research has been initiated to appropriately consider the following concerns regarding participant location, privacy, incentives and connectivity:

1- **Participant location:** The work-organizer selects some participants whose locations are almost independent, assuming that there is sufficiently number of participants available [34]
2- **Participant privacy:** Several privacy techniques require the locations of various participants to be uncorrelated to protect the participant location [35]
3- **Participant incentive:** Mechanism in an MCS architecture framework needs incentives in order to increase the human participant's motivation to take part in the MCS tasks and cover their mobile data cost. Without the incentives mechanism, the participants will be reluctant to collect and deliver the high-quality data [36].
4- **Participant connectivity:** Usually mobile devices are equipped with numerous wireless communication interfaces such as Bluetooth, Cellular, ZigBee, WiFi, and other interfaces maintained by several wireless technologies. Cellular data provides long-range communication infrastructure, while WiFi is the mid-range of communication, and ZigBee and Bluetooth provide short-range communication [31].

For example, to obtain information for participant selection, crowdsourcing application that uses CDR collected from every user on the communication network can be used. CDR includes a detailed record containing extensive spectrum of related information: the telephone numbers, tower

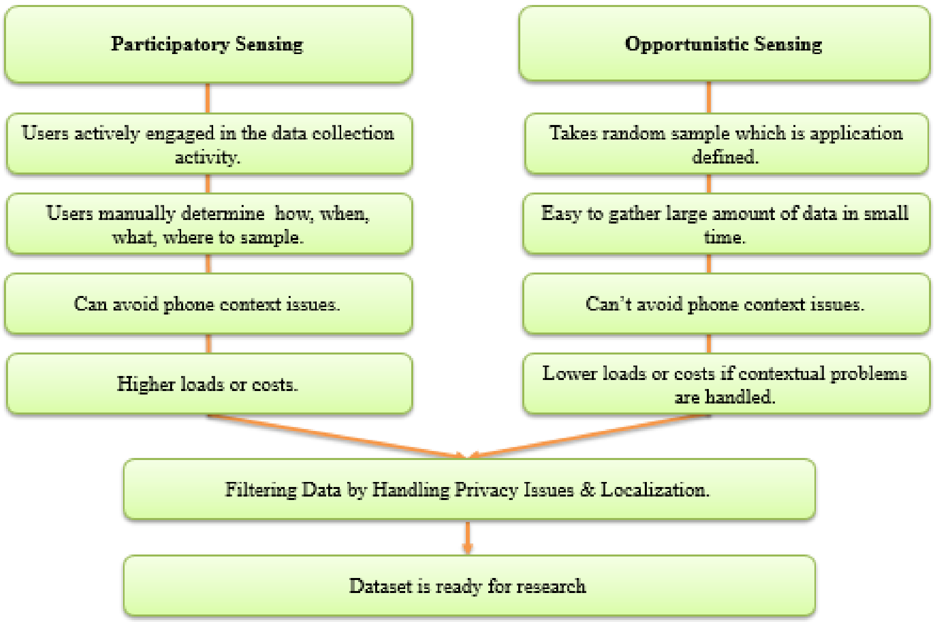

FIGURE 2. MCS paradigm for participatory and opportunistic sensing [15].

TABLE 1. Sample of CDR data fields.

Calling Party Mobile Number	Called Party Mobile Number	Caller Cell ID	Location Area Code	Call Time	Call Duration	Served IMSI
919832747948	919434346553	6182	41708	2012-12-06 14:24:32	00:12:34	4600013511068690

location, calling start time, calling duration, and calling and receiving terminals as well as an international standardized unique number to identify a mobile subscriber called International Mobile Subscriber Identity (IMSI) [28], [37]. CDRs may contain a large amount of information on how, when, and with whom one communicates, hence increase the charges from the mobile phone operators. In addition, most CDRs contain location, and customer's external data such as age or gender, and both information on voice calls and text messages. However, to combine both portions of information into one simple measure is not yet clear. Moreover, it seems that there is a difference in the use of messages or priority between texts and voice calls contained in measures, which takes into account one type of communication [38], [39]. Such collection of personal data makes CDRs a very rich source of data for researchers. Finally, the structure of a social network from CDRs should be continuous, taking into consideration that there is no one-size-fits-all technique available. CDRs are generated in real-time so it can exist almost instantaneously for mining, whereas billing data is available only monthly. Typical CDR data fields are shown in Table 1.

Ren *et al.* [27] propose a Social Aware Crowdsourcing with Reputation Management (SACRM) scheme for participant location. To choose the perfect participant location for the sensing task based on a fixed task budget, the authors propose a participant location selection scheme that is used to evaluate the confidence and cost performance ratio of mobile users for participant location selection. Social elements, task delay, and reputation are all considered. The results show that the proposed reputation management scheme reduces the crowdsourcing cost using the cost performance ratio of the participants for reputation evaluation.

MCS brings some concerns about participating users' privacy. Thus, data privacy mechanisms should be enforced on both the mobile devices and the monitoring center to protect private data, such as the user location, the presence of some people at a given place, and the driving patterns of vehicle drivers. As demonstrated in Figure 2, data privacy enforcement step is applied after data collection regardless of whether participatory or opportunistic MCS. Wang *et al.* [40] proposed a privacy-preserving reputation framework based on blind signatures. While, Christin *et al.* [41] proposed an IncogniSense anonymous reputation framework, which generates a repeat alias by blind signature and then transfers the reputation between these aliases.

For participant incentives, Yang *et al.* [42] described two incentive mechanisms to stimulate mobile user participation in platform-centric and user-centric mobile sensing, respectively. To exploit the utility of the platform, the authors presented a Stackelberg game in [43] based on an incentive mechanism to represent the platform-centric model. For the user-centric model, the authors design an auction-based

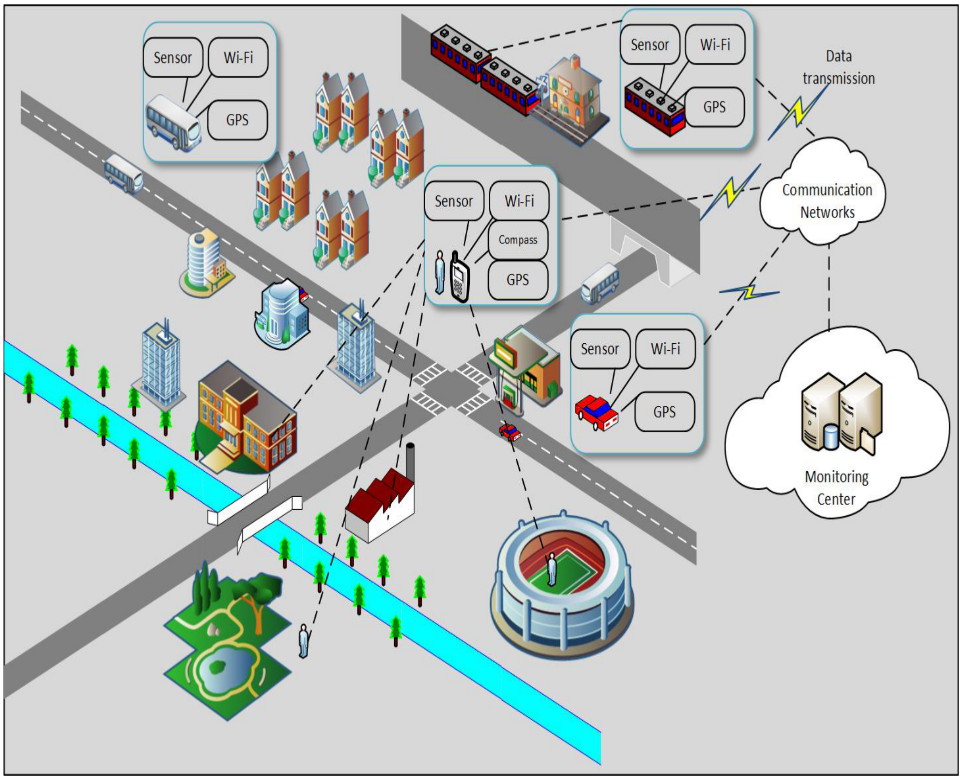

FIGURE 3. An overview of the MCS framework.

incentive mechanism that is demonstrated to be computationally efficient, individually balanced, profitable, and truthful. Meanwhile, Wen *et al.* [44] proposed an incentive approach based on a quality-driven auction with a Wi-Fi fingerprint-based indoor localization system. This model incorporates a theoretical framework into the practical MCS system. Because MCS allows a broad range of mobile applications, the authors introduce a probability model to evaluate the reliability of the provided data. In the best approach of MCS, the worker is paid off based on the quality of data sensed instead of the working time. The authors presented extensive experimental results and proved that the approach is true, reasonable, and public. Moreover, Yang *et al.* [42] addressed the problem of motivating people to participate in a crowd-sensing experiment, with a game theoretic analysis of human behavior and the suggestion of an auction-based approach for incentives. This approach is extended by Koutsopoulos [45] to provide the intention of an ideal compensation portion that reduces the cost of the incentive provided to participants. However, the incentives are not always possible, and a large number of research applications of the crowdsourcing idea rely on people voluntarily helping in the research project [46] or being given non-financial incentives.

For participant connectivity, there exist several communication media that have different types of wireless protocols such as ZigBee (IEEE 802.1.5.4), Bluetooth (IEEE 802.15.1), and WiFi (IEEE 802.11b) as well as Cellular data. Details of some of these protocols are presented later in the paper. Some research have been done on optimizing these protocols, for example Zhang *et al.* [47] propose TrMCD, which is a robust route estimation strategy to extenuate the negative impact of abnormal crowdsourced user routes and recognize normal and abnormal users, as well as to attenuate the effect of the location-unbalanced crowdsourced routes.

III. MOBILE CROWD-SENSING FRAMEWORKS

In a traditional sensing framework, the sensing level relies on a network of dedicated and fixed sensing nodes. The framework introduces many drawbacks such as higher cost, inefficient sensing coverage, maintenance issues and lack of scalability. The new paradigm shift towards MCS addresses the aforementioned drawbacks by replacing the dedicated sensing nodes with the MCS level. The remaining MCS framework levels resemble the corresponding levels in a typical wireless sensor network. Figure 3 shows an overview of the MCS framework, which is divided into several levels: crowd-sensing, data transmission, data collection, and applications on the server side.

1. The crowd-sensing level consists of the crowd-sensing elements, which represent the devices that are selected to be connected to large networks. These devices collect two types of data, mobile sensing data and mobile social network data. The raw data is transferred to the server for information extraction, and the users can decide on which category the data should be pooled. A quick discussion on mobile sensing elements is provided in Table 3.

TABLE 2. Comparisons between sensing groups.

Sensing Group	Sensor Type	Communication Environment	Applications
Healthcare Sensing	Accelerometer, EEG/ECG/ EMG, Pulse Oximetry, Heart rate, Blood pressure, Blood Glucose, and Temperature Probe	ZigBee, Bluetooth, cable, WiFi, WiMAX	Body move, Skin/Scalp, Electrodes Oxygen Saturation, Pulse oximeter, Arm cuff based monitor, Strip-based glucose meters, Body and/or skin temperature
Industry/public Sensing	Accelerometer, flex, power, Vibration, hall, ultrasound, sound, bend, strain, stress	ZigBee, Bluetooth, cable, WiFi, WiMAX	Solar Panel and Inverter, Gas Pressure, Proximity detection, Water Level Sensing, Heating oil tanks.
Environmental Sensing	Air pollution, Water quality,	ZigBee, Bluetooth, cable, WiFi, WiMAX	Physical sensors, Chemical sensors, and Biological sensors
Military Sensing	Security detection	ZigBee, Bluetooth, cable, WiFi, WiMAX	Electromagnetic, pressure, light, energy/signals, explosions, sound,
Mobile Sensing	Touch screens, accelerometers, gyroscopes, GPS, cameras, etc.	WiFi, 3G, NFC, Bluetooth	Traffic monitoring, leisure activities and air pollution control, rich and growing set of social networking applications

TABLE 3. Impact of Zigbee, Bluetooth, Wi-Fi, and GSM/GPRS on MCS.

References	ZigBee	Bluetooth	Wi-Fi	Cellular	Comments
[70, 71, 72]	✓				Not used in MCS due to the lack of ZigBee integration into mobile devices.
[75, 76, 77, 78, 79]		✓			Bluetooth has a very short range that requires higher participants' density for same sensing accuracy requirements.
[78, 81, 86]			✓		Wi-Fi is the most common technology available on mobile devices; however, the infrastructure mode is more technologically developed compared to the Ad Hoc mode. Whereas Ad Hoc mode is typically more suitable for MCS especially in areas not covered by Wi-Fi access points.
[82, 85, 86]				✓	Even though cellular is costly, it is the most widely used technology.

2. Data collection level is responsible for collecting the data from the selected crowd-sensing elements and offers privacy mechanisms to the volunteers. Detailed discussion on data collection is provided under the infrastructure Subsection 3.1.1.
3. The data transmission level defines several mobile networks and communication techniques such as ad hoc or wireless networks [48] (e.g., Bluetooth, Wi-Fi) and infrastructure-based networks (e.g., cellular) that can be leveraged by MCS. The participant uploads the data to the server, where all the applications and services are located. This data transmission should be tolerant to network connectivity outages. Data transmission is further discussed under the communication part in Subsection 3.1.2.
4. The application level consists of a variety of potential applications and services enabled by MCS, such as data visualization. A comprehensive discussion on different MCS applications is provided in Section 4.

In a sensor network, each node has three branches; first, the sensor will sense the environment; second, it performs some local computation on sensed data; and third, it is responsible for message exchange, which is communication [49]. Several classes of sensor groups are used in the MCS applications. Table 2 shows a comparison between these sensor groups, their types, communication environments, and applications used [32], [50].

In the following, we discuss some of the existing MCS enabling platforms that can be deployed on the MCS framework. *Medusa* is one of the most popular MCS applications, which is a mobile sensing framework that has been classified in [51] as a multi-purpose mobile sensing system that introduces a significant performance improvement compared to a standalone system. It allows the use of the opportunistic approach within the crowd-sensing paradigm and enables data collection on the cloud component of the *Medusa* framework. As soon as the data collected is transferred to the server side, there is no room for monitoring or even amending the timeframe of the data collection process. However, synchronization between multiple sensors is not necessary and not recommended due to data privacy and communication security on smartphones.

Another popular MCS application is *Hive*, which is a general software application framework that enables third-party developers to integrate their products in one application. These products include several operations such as data handling, user interactions, mobile or server analytics, and managing user participation [52]. *Hive* specifies new MCS tasks with minimized development effort that can simply

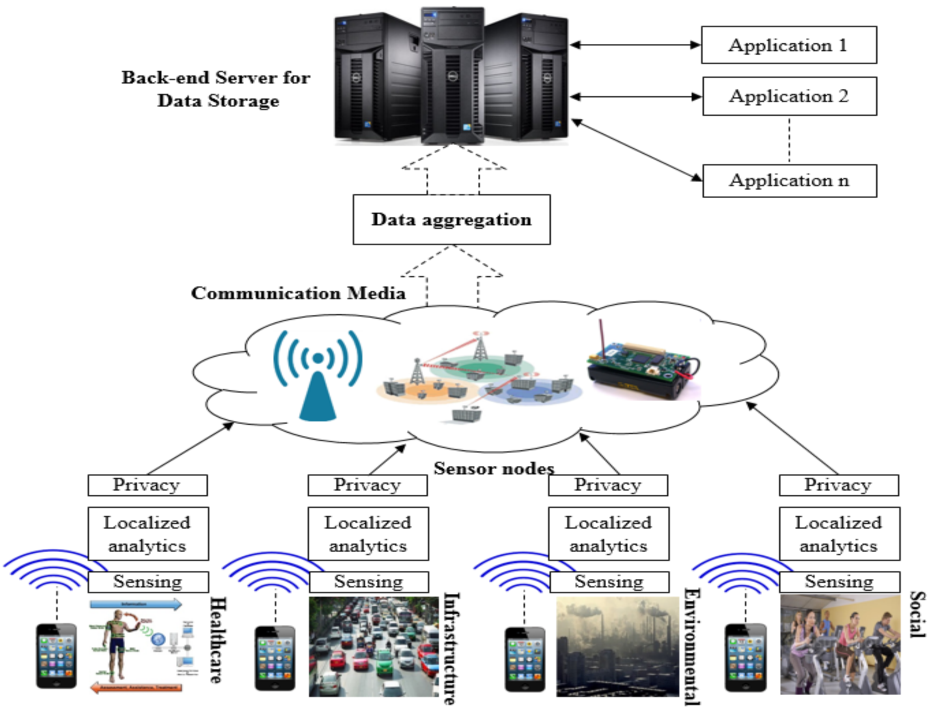

FIGURE 4. Infrastructure required to support the MCS framework.

spread its functionality. Thus, it allows developers to focus only on the novel characteristics of the mobile crowdsourcing application. A practical yet a challenging feature of Hive is to recognize the framework's future generality and extensibility. However, Hive framework is a little less flexible than Medusa in terms of the type of tasks that can be identified and this is due to the consecutive workflow that is only supported by this framework.

A research group from *IBM* [53], University of Illinois, and University of Minnesota has developed a middleware MCS platform that is called Citizen Sense. This platform allows individuals to propose, design, and manage distributed crowd-sensing campaigns. Another MCS application was developed by Google, which is called Science Journal (SJ) [54]. The Science Journal application acquires data from natural sources and apply real-time analytics by utilizing different built-in sensors in smartphones to produce useful information about natural phenomena of interest to the user. SJ allows users to investigate and participate with the world through several onboard sensors in Android phone and Chromebook along with well-matched peripheral sensors.

Restuccia *et al.* [55] developed a new framework to define, survey and analyze the current state-of-the-art of the quality of information (QoI) in mobile crowd-sensing. Information quality is the amount of information received in a period of time and it is specified in reports received during one hour.

The collected data from mobile devices suffer from inaccuracies, noise, and errors. Hence, data aggregation and filtering is needed to improve the accuracy. Indeed, one of the main challenges of dealing with MCS data is related to the problem of separating the characteristic signal from the background noise contaminating the data sets generated by spatially separated sensors. The solution to this problem is to apply the essential redundancy of such simultaneous parallel MCS data sources, which is suitable for the cross-correlation analysis expected to reduce the local background noise, while revealing the true signal simultaneously present in all parallel data sets. However, even if such data pre-processing approaches successfully filter out all unwanted interfering signals, to perform an accurate modal analysis of the frequency response of the system, one still has to address the essential statistical fluctuations affecting the power spectral density (PSD) estimates obtained by Fast Fourier transform (FFT) analytically.

A. INFRASTRUCTURE REQUIRED FOR THE PROPOSED MCS FRAMEWORK

The proposed mobile crowd-sensing framework mandates an infrastructure composed of four main components [7], [8], [56], which are data collection, communication media, data source aggregation/fusion, and data storage and classification. Figure 4 shows the MCS infrastructure and its main components. The explanation of each component can be introduced as the following:

1- Data collection, with the help of an expert group to maintain larger participant base and deliver the required verification of the usability of the collected sensing data.

2- Communication medium, which could be 3G/4G/GSM, WiFi or Bluetooth depending on the required range of transmission.
3- Data aggregation/fusion, which is the process that collects the data from different sensor nodes, and based on a decision criterion pre-processes the data and transfers it to another node/base station
4- Data storage and classification, which is mandated by combination of human and machine intelligence resulting from the participation of human in sensing data. Based on the wealth of data, both human and machine intelligence can be used for data processing.

B. MCS DATA COLLECTION

In MCS, there are two different data source types: mobile sensing and user-generated data in mobile social network services. Mobile sensing is a method of data collection using participatory sensing, while mobile social networks rapidly bridge the gap between online interactions and physical elements [47]. Maji and Sen [37] developed a mechanism to store CDR data in appropriate data warehouse schematic and analytically process the data using On-Line Analytical Processing (OLAP) server tools to understand the prepaid customer's usage and spending and provide appropriate marketing offers. The system also analyzes the telecom data, such as CDR billing, and proposes customer reporting criteria based on ON net and OFF net call frequency to classify appropriate cutomers for different promotional action types. Authors mentioned that the result shows a percentage of retention and attracts other customers from competitors. Wang and Zhang [57] used approach of agglomerative hierarchical clustering to distinguish the abnormal users from normal ones. Authors studied the proposed scheme based on the data of CDR for 10,000 subscribers provided by Chinese telecom operator, which are sampled randomly for one month. The result shows that the abnormal users are distributed in an urban area and normal centralized area. Silva *et al.* [58] proposed a visualization technique called City Image that captures typical transition between Points of Interest (PoI) in a city using publicly available data. Based on the people mobility, the technique provides a visual summary of the city dynamics. Moreover, it explores urban transition graphs to user's movements between city locations. Eventually, City Image is a promising technique that allows for a better understanding of the city dynamics, and helps to visualize the common routine of its citizens.

Social networks have become extremely popular in information technology in recent years because of the proliferation of online social networks sources such as Facebook, LinkedIn and MySpace. These sources can provide information about human mobility, air quality, traffic patterns, and geographical data. The data are gathered by smartphones, vehicles, machinery, medical equipment, and other machines and then sent to the remote server. In this regard, the large-scale user-contributed data opens a new window to understand the dynamics of the city and society, which constitutes the other data source for mobile crowd-sensing There exist several approaches that attempt to use crowdsourcing utilizing diverse data collection techniques. Some of these approaches focus on actions of the services and actions of the citizens in very critical or different time situations. CrisisTracker (CT) is an online system that captures the distribution state of awareness reports based on social media activities throughout large-scale events such as natural disasters. It tracks a huge pool of keywords on Twitter social media and builds stories by gathering tweets that contain these keywords. CT system is used for exploring Twitter with pre-filters based on tweets related to specific disaster and location to provide social awareness from public tweets. It is an open-source web platform and does not use any other social media sources or civil reactions for its sensing [59]. Another open-source crisis-mapping platform called Ushahidi was used on January 12, 2010, when a 7.0-degree magnitude earthquake struck Haiti. Ushahidi provides a way to capture, organize, and share information about dangers coming immediately from Haitians. Ushahidi collects information from two sources, text messages received via mobiles phones, and social media (e.g., Twitter, Facebook, blogs). Eventually, it tries to serve expert organizations with possibilities for demanding citizens or digital supporters to collect important data or to share information [60]. Wu *et al.* [61] present an innovative framework for collecting critical information in a particular disaster area from end-users and mobile devices in order to support timely suitable contextual reconstruction and rescue operations. Both crowdsourcing and crowd-sensing pose the challenge of handling excessive amount of data which requires leveraging big data processing techniques [62]–[64]. Ludwig *et al.* [65] prototyped a crowd monitoring system based on the concept of mobile phone crowd-sensing approach. The design and implementation of the concept of crowd monitoring combine monitoring of physical activities of local citizens with digital social media activities. In addition, it assigns tasks to citizens for emergency services. The tasks can vary from filling sandbags for example to collecting crisis-related information. The authors explored the impact of citizen-generated content on social media during a specific emergency event. They also explored on-site and off-site citizen involvement. Eventually, it led to the implementation of a web-based application called "CrowdMonitor" to use the observed findings to support assessment and collaboration between citizens and emergency services. Finally, with the help of this approach, emergency services can collect information from social media or from local citizens and could obtain a better overview of the event.

C. MCS COMMUNICATION MEDIA

MCS have grown from small-scale with specific applications to large-scale ubiquitous data collection for a wide range of applications. However, a large-scale network is sometimes not achievable due to many factors including economical factors due to high cost associated with large number of sensors, and difficulty of full coverage due to large area. It will need many relay nodes to maintain a complete field coverage and communication connectivity. This will be hard to implement due to both the expensive sensor cost and the distribution, as well as the maintenance cost [66]. Most of the communication technologies in wireless sensor nodes (WSNs) are radio-frequency wireless networking technology-based. WSNs have some limitations such as low processing power, low processing speed (approximately 8 MHz clock speed) [67] very limited storage (few hundred kilobytes), a short communication range and high power consumption. The sensor has a small form factor (mm^3). Minimal energy sources such as batteries have a finite lifetime, and passive devices provide limited energy due to protocol constraints.

Recently, researchers are considering the benefits of mobile sensor networks as an operational and reasonable solution to large scale sensing networks. However, there are several differences between the two sensing techniques [32]. First, MCS relies on mobile devices and smartphones, while WSNs use tiny sensor nodes. This difference allows MCS to perform local processing, as mobile devices and smartphones have more processing power, memory, and energy. Additionally, mobile devices and smartphones use chargeable batteries, which makes local processing for MCS less power-limited (compared with local processing in WSNs). The second difference is the larger scale of MCS (hundreds of thousands or millions of devices and phones across a city or a country) compared with WSNs, which typically have hundreds, or at most thousands, of sensor nodes. Deploying sensors for traditional WSNs at the city-wide level requires at least tens of thousands of sensors. In [3], it was shown that 90,000 sensors and 1,000,000 relays are required to perform citywide (about 900 km^2) environmental monitoring to maintain full area coverage and communication connectivity. The third difference is the human involvement in MCS, which brings some issues such as concerns about user privacy but also brings some opportunities such as the ones emerging from using human involvement in a way that makes the system smarter. Human involvement also brings the issue of incentive policies to ensure user participation in the MCS operation. The fourth difference is the dynamic nature of MCS due to the user mobility, variation of power levels, and changes in user behavior and participation. Finally, the fifth difference is that in traditional WSNs, the sensors are usually stationary whether deployed in deterministic or random locations, while in MCS, the sensors (embedded in mobile devices and smartphones) are mobile and move randomly and independently. This paper presents two of the widely used MCS communication media: wireless access communications network and IP-based core network

For the communication used in the MCS framework, there are two levels of communications: 1) Access communications network 2) IP-Based Core network. The access communications network is part of a telecommunications network that connects customers to their service provider directly. It ranges in diameter from a few hundred meters to several miles and includes all devices between the core network and the user terminal. The core network uses a fiber-optical structure due to its high transmission rate. A core network is the essential component of the telecommunications network that provides several services to customers who are connected by the access communications network. Servers, computer accessories, and applications represent the core network in this study. The following points will present a brief description of the two media and will show in detail the inside and outside communication media that are used in the above framework [66].

1) ACCESS COMMUNICATION NETWORK

In access communication networks, the communication media have different types of wireless protocols such as ZigBee (IEEE 802.1.5.4), Bluetooth (IEEE 802.15.1), and Wi-Fi (IEEE 802.11b) as well as Global system for mobile communications (GSM)/general packet radio service (GPRS). In the following, we will present a brief description of ZigBee, Bluetooth, and Wi-Fi, as well as 3G/4G/5G as sensor communications media

Zigbee is one option enabling the crowd-sensing connectivity through technology based on IEEE 802.15.4 and operates on 2.4 GHz [67]. ZigBee is typically used for low data transfer rate, low power consumption due to low physical data rate, and low-cost wireless applications. It can accommodate up to 264 nodes in the network [68]. Cai and Liang [69] used ZigBee to design and implement an intelligent system for remote health monitoring electroencephalograph (ECG) analysis and diagnosis. ZigBee is designed for self-recovery network acknowledgements, and it can automatically interpret data messages routed in different areas of a network with different radios without user intervention. Gad-ElRab *et al.* [70] propose a flow coverage scheme based on using a modified localization method that relies on less GPS usage and employs ZigBee technology to cover a specific street and complete the coverage requirements. The scheme uses ZigBee technology in order to communicate with the neighbor nodes and estimate the distance between these nodes using Time of Arrival method. The experimental result shows that the flow coverage scheme and localization reduce the usage of location sensors and demonstrates that the proposed coverage scheme reaches the coverage requirements, and finally achieve high localization accuracy. The ZigBee technology is simpler and less expensive than Bluetooth technology. Arai *et al.* [71] defined and measured ZigBee's Received Signal Strength Indicator (RSSI). They analyzed a time-series of RSSI in indoor space to acquire information about crowd behavior (CB). They showed three CB features, which are: density, velocity, and specific patterns. Despite the extended area covered when using the ZigBee technology, it is not supported by modern smartphones [72].

Bluetooth is a wireless technology designed to connect different wireless devices such as telephones, notebooks, PDAs, printers, and computers. Bluetooth provides a short range of 10, which can be increased up to 100 meters, and operates in the 2.4 GHz band with a transmission speed (data rate) of 800 kb/s [73]. Stopczynski *et al.* [74] express the structural design of the Android mobile operating system that allows the Bluetooth sensor approach to obtain participatory data. The approach is used to map the mobility of crowds in large-scale events. The approach is deployed in a large music festival with 130,000 attendees, where a small subset of participants installed Bluetooth sensing apps on their own smartphones. However, this approach has limited scalability and limited spatial coverage. More recent utilization of the Bluetooth technology in crowd-sensing can be found in [75] where the authors have proposed a new context-aware approximation algorithm to find vertex cover that is tailored for crowd-sensing tasks. Authors design human-centric preface strategies to collect information about the participants using sensors. The sensing task refers to the task of collecting opportunistic Bluetooth contacts, or wireless contacts, in mobile ad hoc networks. You *et al.* [76] proposed an MCS application to collect opportunistic sensing data in a limited area using Bluetooth based on Community Information-Centric Networking technology. The application feature supports data integrity and uses IP-less communication as a simple communication model. Several sensors have been deployed with Raspberry Pis and Bluetooth across a building to collect data when a participant walks and draws a map for sensors‘ location in the building. The application fundamentally supports privacy and data integrity of participants. The work in [77] proposed an opportunistic location discovery method that fills the gaps in a user's location trace by deriving location data from other users employing the power of mobile crowd-sensing. Authors used a hierarchical cluster merging approach, which looks for other users using Bluetooth and Wi-Fi scans to detect closeness of users. However, Bluetooth has a very short range that requires higher participants' density for same sensing accuracy requirements.

Wireless Fidelity (**Wi-Fi**) refers to certain types of wireless network protocol 802.11b standards that enable devices to communicate with each other without cords or cables. Wi-Fi enables a better range from the base station, a faster connection, and better security than Bluetooth. Wi-Fi uses the super ultra-low noise S-band (2.4 GHz) to extend the range [78], uses frequency-hopping techniques to connect multiple devices together, and has a range of approximately 1000 feet outdoors [79] Average data transmission rates is 54 Mb/s. Wi-Fi differs from Bluetooth in that it covers greater distances and provides higher throughput, but it requires more expensive hardware and may present higher power consumption [22], [50]. Wu and Luo [78] present a WiFiScout advisory system that integrates a gamification-based incentive system to compensate users who give the most important data based on variety and amount of the contributed data. The proposed system supports three ways: 1) offline search, which allows a user to search around for WiFi, 2) online review, user can use his smartphone to submit a review about his experience on that WiFi, and 3) gamification-based WiFi map, which shows all WiFi access points on a city map. Using Wi-Fi in the MCS is very important, an iSense novel framework has been proposed in [80] for decreasing the unnecessary energy overhead on participatory devices. iSense entirely offloads the localization burden to the crowd-sensing servers. Thus, it reduces the consumed energy at the mobile devices. iSense employs the existing network signaling. Wi-Fi is the most common technology available on mobile devices; however, the infrastructure mode is more technologically developed compared to the Ad Hoc mode. Whereas Ad Hoc mode is typically more suitable for MCS especially in areas not covered by Wi-Fi access points.

Cellular communication technology, GPRS supports mobile data service on the 2G (GSM) and 3G cellular communication systems [50], [79] Moreover, 4G offers joint services such as voice, data, and multimedia at data rates of up to 100 Mbps as well as pervasive mobile access to a wide variety of user devices and independent networks. Foremski *et al.* [81] propose a location-tracking algorithm that improve crowd-sensing data for modeling cellular networks. To measure human location and signal strength in cellular networks, a practical application has been developed to perform the measurements of human mobility and signal levels without user interference and with minimum power utilization. However, authors mention that many users are not willing to participate in crowd-sensing experiments. They also mentioned that their system decreased the battery lifetime by around 20%. Another research in [82] discusses the challenges that face cellular providers as the number of cyber-physical system (CPS) devices trying to access the cellular spectrum increases dramatically. This work presents a device-to-device (D2D) communication technology for CPS communication over current network infrastructure through the use of fifth generation cellular networks. Masek *et al.* [83] develop a next-generation traffic management system in a smart city environment that incorporates the Internet of Things (IoT) technologies with low-power and long-range 5G embedded devices. They started by data sensing that utilizes heterogeneous road monitoring tools that measure, and send the traffic information, vehicle speed, etc. to the traffic management entity. The results show that the use of modern devices, such as Raspberry Pi2, satisfies the requirements for future traffic management systems in smart cities. Sun *et al.* [84] present a secure and privacy protective object finding application via mobile crowdsourcing using 4G/5G. They proposed an approach called SecureFind that obtains the finding request from the service provider. Hence, 4G and 5G cellular networks authentication and privacy schemes are required to protect user identity, and location privacy among others. Another interesting system utilizes location-based social network (LBSN) on Cellular systems is called *Check-Inside* [85]. This system provides a fine grained indoor localization. It leverages the crowd-sensing data collected from mobile devices during the check-in operation. In addition, it extracts knowledge from the LBSN to connect a location with a logical name and a footprint. The system uses Wi-Fi in

TABLE 4. Technology characteristics for Zigbee, Bluetooth, Wi-Fi, and cellular.

Category	ZigBee	Bluetooth	Wi-Fi	Cellular
Cost	Low	Low	High	High
Frequency Band	868/915; 2.4 GHz	2.4 GHz	2.4; 3.6; 5 GHz	850/900; 1800/1900 MHz
Range	5-30 meters	10 meters	100 meters	2-35 km

two modes: ON and OFF. When the Wi-Fi is ON, this leads to a higher accuracy compared to the use of cellular localization. Experimental results show that the CheckInside system can achieve the actual participant's location. Even though cellular is costly, it is the most widely used technology. Costs are expected to drop with the advent of 5G and its support for IoT through the massive machine type communications (mMTC) paradigm. Table 3 and Table 4 show the comparison between ZigBee, Bluetooth, Wi-Fi, and Cellular in terms of impact on MCS and technology characteristics [22], [82], [86]–[88].

2) IP-BASED CORE-NETWORK

The core network is the vital component of a telecommunications network that offers several services to customers who are connected to the access network. Usually, the term core network is used for service providers. It offers routes to exchange information between different sub-networks. Generally, it denotes the high-capacity communication facilities that interconnect fundamental nodes [68].

The core network offers several features like aggregation, authentication, switching, charging, service invocation, and gateways. The core network consists of IP-based, cloud, or long-haul networks based on microwave, optical, or satellite technologies. **IP** is the internet protocol (IP) that refers to part of the TCP/IP protocol. **Cloud** is a type of computing that depends on sharing resources rather than having dedicated local devices to manage applications [89]. In other words, it describes services delivered over a network by a group of remote servers. There are three benefits for cloud computing: 1) Self-service Supplying: for any type of workload, particularly on-demand, the end user could turn up the computing resources; 2) Flexibility: depending on computing needs, companies can increase or decrease their available infrastructure as needed; 3) Pay per use: allowing users to pay only for resources needed for their current workload. Finally, **long-haul networks** are groups of commonly distributed computers that are connected through a collective communication network. Communication in such systems is moderately slow and changeable, normally through telephone lines, microwave links, and satellite channels [90]. However, several services are provided through long-haul networks for users. These services include the capability to send or mail information from one site to another and post news on bulletin boards so that any user can read them

D. MCS DATA SOURCE AGGREGATION/FUSION

MCS also explores the data fusion from different sensor nodes acting as spatially distributed data sources [91]. Therefore, using MCS, both online and offline-denoted data can be leveraged by participants exploring through-space data fusion to develop modern applications. Several distinctive research challenges grow from the mobile crowd-sensing paradigm such as proper incentive mechanisms, data collection, and through-space data fusion. Moreover, MCS represents a mixture of human and machine intelligence that is not explored so far. A data fusion node collects the data from numerous nodes, and based on a decision criterion, it fuses the data with its own and transfers it to another node. The advantages are that it reduces the traffic load and conserves the battery of the smartphone. The data comes from different sensors, databases, or more accurate data sets. The data fusion algorithm is very important for any mobile monitoring system [92], [93]. Finally, data fusion takes place closer to the sensors, especially for raw sensor data, to reduce the network load resulting from many sensors collecting data from different locations.

Data fusion significantly improves accuracy of the statistical model by combining specific information of several heterogeneous sensing systems, where the datasets are represented in different feature spaces. This makes it hard to investigate relationships between the heterogeneous data, even in case the datasets are related to each other. A statistical approach to data fusion combines sensor datasets in a robust way as they benefit from variances between devices and their complementary features [94]. Castrignanò *et al.* [95] combined multiple sources of information in a statistical framework. The main advantage of the statistical framework is that straightforward probability models are used to describe the different relationships between sensors, taking into account the uncertainty behind it and the change of support. However, there are several statistical methods that analyze heterogeneous data based on Bayesian and machine-learning methods. Other research work in [96] introduces a novel model using heterogeneous data fusion through a fully convolutional neural networks to acheive semantic labeling. The authors presented the residual correction as a way of learning how to fuse predictions from a dual stream structure. The result shows that the residual correction is capable to recognize accurately, which stream is trusted for different classes.

E. MCS DATA STORAGE AND CLASSIFICATION APPLICATIONS

This section discusses data storage, preprocessing, feature extraction, detection, and classification to measure the data accuracy.

The data storage and classification application on the server side is a very important element of MCS, to detect and classify the collected data accuracy. The architecture framework has two parts, the client or mobile sensing node, where the acquiring client application runs, and the server, where the collected raw data are stored and kept for future use. The client application regularly acquires the data, applies simple preprocessing, and transfers it to the server over a secure Internet connection. On the other side, the server immediately places the received data into a queue that is later processed in a separate thread. Local storage and processing modules manage the acquired raw data from the sensor. This allows nodes to support an off-line mode for temporary local storage. When network connectivity is accessible, the locally stored data is transferred to an external server for further processing [88].

Processing of raw collected data is very important to reduce the transferred data size, which ultimately increases the sensor battery lifetime. However, the normal readings from sensors may not be proper for direct use by applications, depending on the quality of the raw data and the needs of the application. There is a need for local analysis of data to perform specific processing of raw data on the mobile sensor node. This analysis produces intermediate results, which are transferred over the core network to the storage. There are two motivations for such local sensor analysis. First, this processing eventually will reduce the transmitted data therefore less energy consumption and less bandwidth during the transmission. Second, it decreases the amount of processing that is performed at the server side [91]. Data processing has been simplified and reorganized in recent years using data centers and high-speed cloud computing capabilities. Data processing is automated to the extent that heavy processing applications such as pattern recognition and image processing are executed in near real-time [92]. Before saving data to databases, stream computing technology has evolved to provide real-time analysis of huge size of data to help with timely decision-making. Some continuous streams of data may originate from sensors, cameras, news feeds and a variety of other sources to be classified, filtered, interconnected, and transformed into informed decisions.

Feature extraction is a process that produces a set of the most relevant features that represents the information for analysis and classification in an efficient way. Feature extraction plays a significant role in identifying most data. Obtaining useful and discriminant features depends largely on the feature extraction method used [92]. The objective of feature extraction is to increase the performance and efficiency of the analysis and classification. This can be achieved through removing redundancy and variability in the data that is of little or no value in the classification or discarding entire data sets if applicable. Another option is restructuring the data in the feature space to optimize the performance of the classifier [92]. Finally, it is possible to extract spatial information, which is critical to target similarity or identification. The main advantage of these features is the reduction of the dimensions of the cross-correlation sequences for use as inputs into individual classifiers. The motivations of these processes are to minimize the number of features and maximize pattern discrimination. As the increased number of features is not necessarily good; because they increase the redundancy in the features which might confuse the classifier, so the ideal case is to generate a minimum number of discriminant features. Feature extraction techniques can generally be categorized into time-domain or frequency-domain-based according to the features used. These techniques were used in several research work [50], [97], [98]. Time-domain features are easily computed, and their time complexity is usually manageable [98]. While, Frequency-domain features are obtained by transforming data from time into their basic frequency components using FFT [99].

Detection and Classification play an essential role in timely analyses. There are two types of detection such as event detection and object detection. The event detection is used to detect the occurrence of a certain event and the significance of the occurrence, while an object detection, detects the existence of an object and possibly some of its properties such as size, color... etc. A classification is an ordered group of correlated categories used to organize data according to its similarities. Each class must have easily recognizable features that should be few and not overlapping with those of other classes. The overall accuracy of the classifier represents the degree of closeness of the measured results to the true values [100]. Specificity and sensitivity are two factors that affect the classification accuracy, defined as functions of the true and false positives and negatives. A false positive (FP) refers to the condition in which the results are incorrectly perceived as positive, while true positives (TP) are test results that show correctly perceived results [50]–[98].

Similarly, a true negative (TN) is defined as the correct behavior to detect the normal condition; while a false negative (FN) is the incorrect detection of the normal condition [50]. Specificity in classification refers to the ability of an assessor to measure a particular substance [98]. Specificity, also known as a class precision, is defined as the percentage of true negative tests within the total number of negative tests. The sensitivity, also known as a class recall, in classification testing represents the smallest amount of a substance in a sample that can be accurately measured by an assessor. Sensitivity is defined as the percentage of true positive tests within the total number of affected (positive) testes. Therefore, the specificity, sensitivity, and overall accuracy of the classifier can be defined as [50], [98], [100]

$$Specificity = \frac{TN}{TN + FP}, \tag{1}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{2}$$

and

$$Accuracy = \frac{TP + TN}{TN + FP + TP + FN} \times 100, \tag{3}$$

where TP, FP, TN, FN are the true positives, false positives, true negatives, and false negatives, respectively. Both positive and negative terms are denoted as the classifier's prediction or expectation and true and false refer to whether that

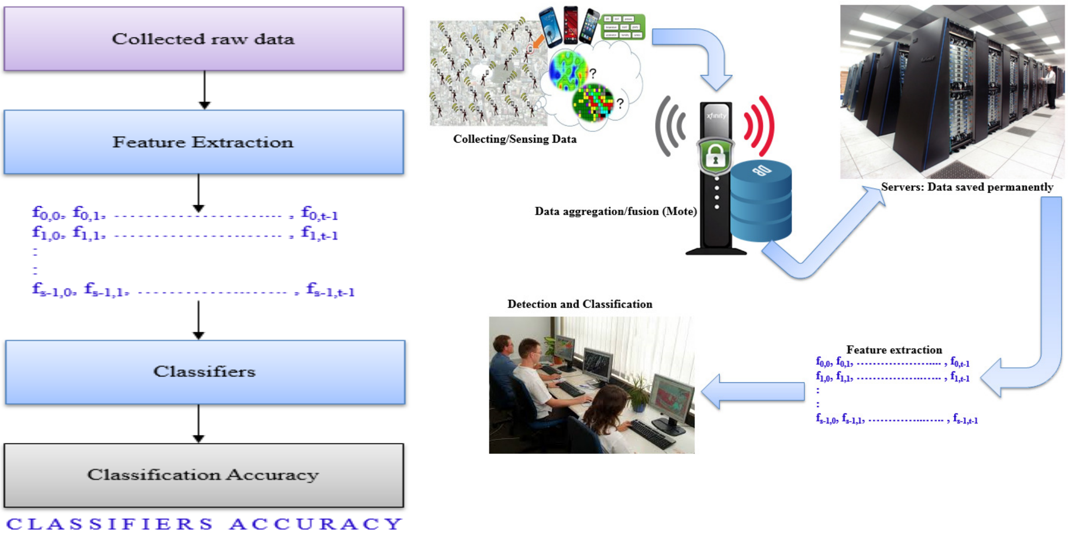

FIGURE 5. Feature extraction and classification.

TABLE 5. Crowd-sensing types of measured phenomena [32], [66], [69].

MCS applications	Used in	Examples
Healthcare	Measuring the healthcare vital signs	Measure heart rate, EEG, ECG
Environmental	Measuring the parameters of the natural environment	Water levels, air pollution, wildfire habitats
Infrastructure	Measuring the status of the public infrastructure	Traffic congestion, road conditions, bridge faults, structural health monitoring
Social	Measuring data about individual social life	Cinemas visited by an individual, daily exercise or sports

prediction corresponds to an external judgment/observation. Consequently, these terms compare the results under the test of the classifier with trusted external judgments. The procedure of feature, detection and classification is shown in Figure 5

IV. MOBILE CROWD-SENSING APPLICATIONS

In this section, we will introduce a brief summary of available mobile crowd-sensing applications, describe their characteristics, demonstrate several research challenges, and finally discuss possible solutions. Generally, MCS applications can be classified into two groups based on the type of phenomenon being monitored: personal and community sensing applications. In personal sensing applications, the phenomena pertain to an individual, while community-sensing applications apply to monitoring large-scale phenomena that are not easily measured using an individual application. These applications link computing devices together, share data, and then extract information to map phenomena of common nature, which generally belongs to one of the following four types: healthcare, environmental, infrastructure, and social life [66].

In healthcare monitoring, smartphones are capable of connecting patients with medical services through mobile communications networks for sensing and diagnostic capabilities. In environmental applications, some of the main phenomena to be sensed are water levels in creeks, air pollution in a city, and wildlife habitats in order to monitor their behavior for further study. In infrastructure applications, the main phenomena to be sensed are traffic congestion, road conditions, parking availability, and outages of public works Finally, social life, where individuals share sensed information between themselves. For instance, individuals can share their exercise time in a day and compare their daily exercise routines. Another example is that individuals can share their exercise data and then compare their exercise levels with those of the rest of the community [32]. Moreover, the individuals can use this comparison to help enhance their daily exercise routines. Table 5 shows the summary for the four different crowd-sensing types of measured phenomena.

Mobile sensing and smartphone devices deliver an appropriate platform for the four categories of MCS monitoring applications listed in the Table 5.

A. HEALTHCARE

Healthcare monitoring uses sensors to monitor patient vital signs both locally and remotely. It offers enhanced patient care through early detection of adverse health conditions. It can influence patients' behavior to improve their health [101]. For a wide range of patient conditions, biosensors offer point-of-care monitoring. These sensors read some specific measurements such as heart rate, blood pressure and body temperature; and monitor certain medical conditions such as diabetes or seizures. The medical data collected from biosensors of the patient is forwarded to medical facilities or specialists for analysis and diagnosis Smartphone manufacturers are increasingly interested in healthcare applications, which led to the integration of more sensors in mobile phones. These devices are widely accessible and continuously connected to the network. They also have processing capabilities that exceed all of the traditional sensors used in WSNs. The combination of the powerful processing and connectivity of smartphones offers low-cost access to health services from an increasing range of healthcare applications [21], [48], [50], [98].

According to mobile research specialists (research2 guidance), smartphone applications for the mobile health industry are successfully installed and have reached 500 million of the total 1.4 billion smartphone users in 2015. Presently, there are more than 17,000 mHealth applications in major app stores [102]. Research in the domain of remote health monitoring over the past few years can be categorized into three main streams: how data is collected, how data is communicated, and where is the data processing performed. Foremski *et al.* [81] the research focuses on the role of mobile phone devices and their related technologies to monitor the patients. This role was limited to a mobile client terminal used to browse healthcare records. However, with the extensive availability of smartphones a range of new smartphone-based medical applications became available. These tools provide the user as well as the care provider with essential tools that help monitoring and diagnosing certain health situations that requires continuous care.

In the aforementioned scenarios all the discussed healthcare applications are personalized rather than belonging to MCS. However, we envision that MCS can serve the healthcare sector from the point of view of medical practitioners' clinical research and treatment assessment statistics, which is a major pillar of medical advancement. An example of using MCS in medical clinical research is the *TrackYourTinnitus* project [103], where MCS has been used with data anonymization to provide datasets on large numbers of patients on daily basis with low cost enabling ubiquitous clinical trials research. The same model can be applied to clinical trials related to any of the various smartphone-based sensing applications discussed earlier in this Subsection. Thus, MCS would allow the transfer of the collected personal mHealth information to a centralized cloud, after appropriate anonymization (as discussed in Section V.B). Then, big data, cloud computing, and data analytics could be used on a collective level to study the population's health status, gather information about disease proliferation, and take appropriate measures.

B. ENVIRONMENTAL

A few years ago, the trend towards clean world technologies led to a large flood of environmental senor technologies. The environment needs to be sensed and monitored to deliver information about the variation of environmental conditions such as temperature, humidity, carbon-dioxide levels as well as all pollution sources. Increased industrialization and extensive agricultural activities due to the growth of population, have led to deterioration in the air quality due to emission of undesired materials into the atmosphere. The effect was not limited to air but it also affected the water quality which reached unprecedented levels of pollution in decades. Hence, natural life and environment is negatively affected. A mixture of fixed localized sensors and mobile smartphone sensors can provide a monitoring context from both personal and local perspectives. This includes many motivating technologies that have become more and more important [6]. The demand on wide range of applications in environmental sensors has increased in recent years. The environmental sensing category could be divided into three different groups: physical sensors, chemical sensors, and biological sensors. **Physical** sensors measure physical quantities such as dynamic forces, light, temperature, sound, magnetism, and electromagnetism. **Chemical** sensors measure humidity, gas, ions, CO, as well as chemical process and oil refining products. Finally, **Biological** sensors measure immunities, microorganism, tissues, bacteria, viruses, proteins, and enzymes [33].

Motion sensors and air pollution sensors are integrated into the air quality monitoring for both indoor and outdoor environments. The exposure to air pollution while being on the move in cities relies heavily on the choice of the means of transportation as well as the route chosen. High levels of air pollution are easily identifiable by the human sensory system (e.g. eye, nose). Similarly, human ears can sense high noise pollution levels [104]. Because people are able to easily sense the air pollution with smartphone devices while being on the move within the city, this may have an impact on mobility behavior as well as their awareness of air pollution. An increased awareness of air pollution will lead to people examining their own mobility behavior with the resulting impact on air quality [105]. Sensing air quality in real-time and providing it as an online service will lead to a crowdsensing city-wide air pollution map. However, to obtain a robust and extensive database of the air-quality in the city, the crowd-sensed data stream must be accompanied with measurements from official air quality monitoring devices as well as measurements from small sensing devices fixed on public transportation vehicles that move across a city regularly [106]. The research team in [107] developed an iPhone application called *CreekWatch* in order to monitor the local crisis with the support of crowdsourced data about the quantity of water, rate flow, amount of trash, and depiction of the channel. Each single user plays a key role in enhancing the quality of water resources by sharing captured data with water control panels.

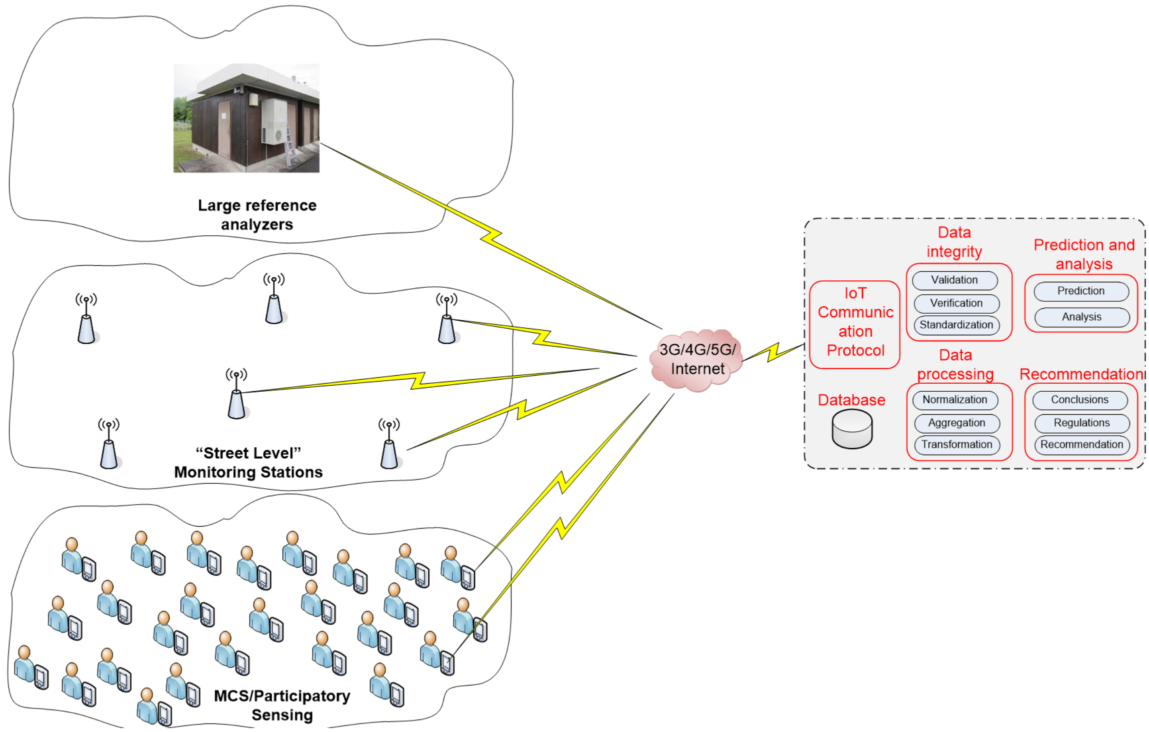

FIGURE 6. Schematic of an integrated air quality monitoring network, with a single platform receiving data from multiple sources of different types. Bottom Layer: MCS / Participatory sensing; Middle Layer: medium-sized sensor nodes ; Upper Layer: Large standardized analyzer stations.

Consequently, to reach an integrated air quality monitoring network targeting improved urban life quality, data needs to be gathered from multiple sources of different types:

a. Reference analyzer based, standard compliant, large monitoring stations, that can be deployed in limited numbers due to cost and size constraints;
b. Medium-sized sensor nodes with acceptable accuracy and reasonable cost, that can provide street level pollution information in densely populated areas or localized details at certain road intersections for example;
c. MCS/participatory sensing through the involvement of people sending "personalized" pollution information. This can be achieved through smartphone sensors or small portable sensors that can be as small as the size of a wrist watch. Although currently most of these sensors lack the accuracy level of reference analyzers or medium sized nodes, their performance is rapidly improving. They can be used to monitor personalized pollution exposure and track the impact of air quality on specific individuals.

The third category of sensors can be used in order to give to the individual the possibility of becoming an air quality observation platform, thus building a citizen observatory through MCS. Collecting the data from the various sources (analyzers, WSNs, and MCS/participatory network) under a single platform allows the implementation of advanced quality assurance (QA) and quality control (QC) methods: data from standardized analyzer stations can be used to validate the measurements of the medium scale sensor nodes, and the measurements of these latter nodes can be used to check/correct/validate the measurements from the small portable sensors, which are the least accurate. Hence, data validation techniques can be automated, with the system receiving and integrating information from three layers, as shown in Figure 6 (the layers correspond to the same geographical area and overlap in reality. They are separated in the Figure for clarity).

Consequently, MCS can pave the way towards more spatially and temporally accurate environmental information that will enhance the ability to prevent and mitigate air pollution in urban areas. It will allow reaching very local environmental scales based on small sensors, wireless networks and phone applications. Furthermore, new information about temporal and spatial variability of pollution may allow to more accurately estimate both contribution of individual sources and the effects on human exposure: this knowledge can then be used to prevent pollution or mitigate the effects.

C. SMART CITY

A *smart city* aims to increase the quality of life in the city by making it more convenient for the residents to find information of interest and providing such information in a way that is easily understood [108]. To form a smart city, several interconnected systems are necessary to provide the required services (healthcare, infrastructure, environmental, social netwroking) based on intelligent technologies. According to Navigant Research report on Smart

Cities [109] the worldwide smart city market is expected to grow at $88.7 billion dollars by 2025 from $36.8 billion in 2016. The report shows that this market was escalating from the cooperation interconnection of five key industries and service sectors: water, buildings, energy, mobility, and government. The report shows that the worldwide revenue forecasts for smart city technologies, divided by industry and region spread through 2025. The report also studied the significant market drivers and challenges correlated to smart cities, key business models used to fund smart city projects, and the competitive landscape. However, for a numeral of technical, financial, and political barriers the Smart City market has indeed started taking off. For realization of smart city using Internet of Things (IoT) the research in [110] proposed a unified framework includes a complete urban information system. The system components vary from the sensors level and network support through data management and Cloud based consolidation of concerned systems and services, and form a transformative part of the current cyber-physical system. A taxonomy has been devised in [111] to bring the best summary of the IoT paradigm for smart cities, network types, and possible openings and major requirements. This research also presented the up-to-date efforts in this filed as well as focused on the current open source IoT platforms for recognizing smart city applications.

Smart city emphasizes the collaboration between the government and the society in several fields that affects the citizen in his daily life such as, economy, mobility, environment, and governance. The idea of a smart city can offer high-quality services to the population to reduce the operational cost through information and communication technology [112]. A smart city needs to effectively use public resources and enhance the quality of services, while decreasing the public administration operational cost. Smart cities need to consider people daily life conditions, environment protection, safety, and city services as well as industrial and commercial activities. All of the proposed solutions should use collected data and a way to meet the demand for high quality services [113]. The city services are registered and reported through collected geo-content, such as waste disposal, damage of car parking, road condition, and traffic lights. Since the purpose of smart cities is enhancing the citizens' quality of life, the role of people in a smart city framework through participatory sensing and MCS is of utmost importance. For example, Smart City sensing is an application that can sense, report, review, and discuss local problems through social media and participatory sensing [114]. Mobile crowd-sensing becomes a significant part of any smart city by leveraging the national mobile services to monitor the city provided services. MCS applications include monitoring the city noise [115], [116], traffic congestion [117], emergency incidents [118], weather [119], population density [120], and even detecting earthquakes [121]. Mainly, these applications depend on mobile sensors available with users or installed in vehicles, however, the user's privacy will be at risk at such locations and times. Nowadays, smartphones with powerful embedded sensors have facilitated new applications such as real-time road-traffic monitoring, air and noise pollution, crime control, and wildlife monitoring through pervasive Internet connectivity.

As a case study, *TreSight* [122] is an example of smart city big data application that uses data analytics and Internet of Things (IoT). Authors used the concept of smart and connected communities for a community to live in the present, plan for the future, and remember the past by highlighting MCS as the most important IoT technology. TreSight was proposed to develop the smart tourism and sustainable cultural heritage in the city of Trento, Italy.

Gao *et al.* [123] the research work proposes a system called Jigsaw that reconstructs a floor plan by integrating data crowdsensed from mobile users such as place of image capturing, accelerometer, and gyroscope data. This data is integrated to figure accurate indoor floor plans that increase localization performance. Zhang *et al.* [124] proposed a self-contained indoor navigation system (GROPING) isolated from any infrastructure support. GROPING utilizes MCS to build floor maps without the need for digitized maps of individual places. GROPING was able to deliver adequate accuracy for localization and provided smooth navigation through 20 participants in each floor in a big shopping mall.

D. INFRASTRUCTURE

Infrastructure comprises the essential facilities, such as roads, water supply, bridges, and telecommunications, as well as all other structures serving a country, city, or region [125]. This can be defined as the real components of related systems to provide services to sustain, or enhance people daily life conditions. The evaluation of the condition of civil infrastructures and critical facilities is especially important after natural disasters such as earthquakes, hurricanes, or manmade disasters, namely terrorist attacks [126] Two of the most common infrastructure MCS applications are drive sensing and structure health monitoring. In the following we provide detailed description for the latter.

1) DRIVE SENSING

Traffic monitoring is a significant participatory sensing application, where GPS enabled smartphones can offer priceless information about traffic conditions. It can sense driver/vehicle activities and behavior, sudden traffic events and risky/aggressive driving. It can also sense the traffic status (dynamic travel time, traffic congestions, etc.). Eventually, it will monitor the road conditions including potholes, road bumps, and slippery roads (using sensors attached to vehicles), vehicle fuel consumption, and emissions. Moreover, authorities can perform analysis of the collected data in terms of the detection of real-time traffic events, dynamic black spots, and can generate profiles for bad driving habits [17], [26]. Other recent work, Basudan *et al.* [127] suggest a new idea for privacy preserving for vehicular crowdsensing. The idea is to introduce a certificateless aggregate signcryption scheme, (technique to accomplish both encryption and signature in one logical step), which is highly efficient in term of low communication overhead and fast verification. The authors developed a road surface condition monitoring system consisting of a control center, smart devices, and a cloud server.

2) STRUCTURE HEALTH MONITORING (SHM)

Structural health monitoring research is based on the use of sensors to detect and localize damage through structural responses as well as patterns of vibrations induced in the structure. SHM itself is not a new concept. A close look at civil infrastructures everywhere and their importance shows how essential it is to use new technologies to monitor these structures on social and economic life. That leads to a great need for advanced methods for monitoring such structures and detecting (or even predicting) the damage [128]. Unfortunately, the normal practice these days is to detect/predict the damage based on visual inspection using very traditional methods such as nondestructive testing, reinforcement detectors, and using hammers to check for delamination. Not only are these tasks labor-intensive, but they are also carried out infrequently. Moreover, the traditional methods use personal computers cables that need to be deployed at the inspection site. This will increase the cost as well as the complexity of installation and maintenance. Researchers tried to save the cost by using wireless sensor networks (WSNs) as their main technique, which improved and facilitated the deployment of these WSNs. Compared with conventional methods, the use of WSNs in SHM provides the same functionality at a much lower cost, which enables much more efficient monitoring. Hence, SHM based on WSNs has recently gained growing interest, due to its efficiency and accuracy. Several structural health-monitoring techniques have been studied and investigated in the last three decades [129], [130]. These approaches include vibration-based and time-frequency wave propagation [129], localization in wireless sensor networks [130], fiber-optic sensors and networks [131], optical inspection methods [132] and optoelectronic scanning [133]. However, there are still several significant research challenges in SHM using WSNs that need to be investigated.

One of the infrastructures that need continuous monitoring are bridges as they are vulnerable to natural wear and their collapse leads to disasters. Monitoring structural health of bridges is one of the goals of infrastructure monitoring [125], [126]. Elsersy *et al.* [128] proposed SHM model using WSNs to monitor and detect the damage condition of the real bridge. The model have several components such as sensor nodes, shaking table with its amplifier, and real concrete bridge. The sensors were fixed on the scaled down bridge that is fixed on the shaking table. The experiment was conducted in the case of normal bridge, single-side damage, and double-side damage. The mode has detected the damage in terms of acceleration on different nodes at a particular excitation frequency. One of the challenging problems, is the identification of the modal parameters of civil engineering structures, mode shapes, from ambient excitation It can be addressed by sophisticated techniques such as the basic frequency domain (BFD) and frequency domain decomposition (FFD) methods [134] or the signal to model ratio (SMR) statistical estimator [135].

MCS allows complementing the role of traditional WSNs in SHM by using the sensors in the drivers' smartphones to monitor the structural health of bridges. In fact, smartphones present an important opportunity to form a low-cost citizen wireless sensor network and introduce big data for monitoring structural reliability and safety under operational and extreme loads. The research work in [136] presents a SHM platform integrating smartphone sensors, the web, and crowdsourcing for a prospective crowdsourcing-based SHM platform. They developed an iPhone (iOS) application to allow citizens to use their smartphones sensors for measuring structural vibrations, and then upload the data to a central server. They also developed a web-based platform to automatically collect and process the data then store the processed data. However, some challenges were noticed related to citizens such as location, connection conditions, and sampling length. After a major event such as an earthquake for example, the collected data could be very useful for performing a quick assessment of structural damage in a large urban setting. For measuring structural vibration, the research work in [128] and [137] discovered that smartphone accelerometers could monitor structural vibrations under normal and extreme loads. They tested smartphones under sinusoidal wave excitation with varying frequencies in a range of civil engineering structures. The experiments for normal and heavy loads show that the reference and the smartphone sensor measurements are close to each other in time and frequency domains. They also demonstrated the smartphone sensor's ability to measure structural responses ranging from low-amplitude ambient vibrations to a high-amplitude seismic response. Another research in [132] proposed a cluster-based data aggregation architecture to facilitate application development for efficient SHM. The authors developed a modular middleware on sensor nodes and an SQL-like user interface to configure the SHM in runtime mode. A three-level structure was built to filter unwanted samples and extract features from raw measurement data. The multiple measurements are then combined from different locations.

E. SOCIAL NETWORKING

Social can be categorized into two categories: social network and social sensing information. In social network, the users can share their information between each other by utilizing many systems like LinkedIn, Twitter, Facebook, and Yahoo! Answers [138]. A large number of individuals connected in a social network can deliver best answers to complex problems as compared to a single individual.

While in social sensing, the MCS application collects data about personal activity and sends it to the remote server for further processing. In such system, the users can share their information only among certain groups of friends or community for privacy purposes. Since most of the data are sensitive information such as personal health, location, pictures and videos; the community approach is the best one to collect and integrate data from several people [5] Morgan-Lopez *et al.* [139] examine the single and joint predictive validity of linguistic and metadata features in predicting the age of Twitter users. Authors created a dataset that describes Twitter users across several groups of ages such as youth, young adult, and adults, then collecting their birthday. Finally, examine the predictive validity of the following features: language only, metadata only, language and metadata, and phrases from other age-validated dataset. The result suggested that examining linguistic and Twitter metadata features for prediction may be helpful for public health and evaluation research.

In [140], an application called MobiGroup, combining mobile computing with social networks, is a group-aware system that delivers assistance during several group activity organizational stages. MobiGroup is a smartphone sensing system to endorse current activities based on user activity distance and interaction dynamics in a community. Also, it uses smartphone sensing to capture online/offline social events and enables group formation and management. Bulut *et al.* [141] present a crowd-sensing application for observing and predicting the waiting time to enter a coffee shop called LineKing. LineKing is used on daily basis to monitor and estimate the wait time for hundreds of users at a coffee shop in the University at Buffalo, SUNY. In addition, it uses uninterrupted streams of accelerometer data provided by participants to detect the waiting time of users. Another MCS application is FlierMeet [142] that applies crowd-powered sensing system to collect and share public information in cross-space using the built-in sensors of smart mobile phones. Authors utilize several contexts (e.g., flier publishing/reposting behaviors, spatio-temporal info, etc.) and written features to group and categorize related reposts. FlierMeet application captures the data through 38 recruited participants and 2,035 reposts during eight-weeks. The results proved that FlierMeet is an effective and convenient application for flier category tagging.

Another interesting discussion is how to correlate information extracted from smartphone data with other information from demographics or socio-economical status to predict and anticipate better results for the individual user. The study of the population based on several factors such as race, gender, age, education, income, marital status, job, religion, birth rate, death rate,.., etc. is called demographics. Frequently, demographical studies are used by governments, corporations, and non-governments to learn more about population characteristics for several purposes, plus policy development and economic market research [143]. The factors of family demographics help in describing the level of human capital in a family. In [144] the work assesses the separate and common predictive of lingual authenticity and metadata approaches to predict ages. The work was based on both Al Zamal *et al.* [145] and Nguyen *et al.* [146] research work which inspects the common prediction of annotation age and labeling. Their objective was to increase the validaty of age prediction in Twitter.

F. TOURISM

Tourism could be significantly empowered by crowdsensing, crowd management, context-aware and location-aware services. In fact, these techniques allow tracking tourists for safety purposes and also for providing contextual information that can enhance their experience: information about the nearest restaurants, coffee shops, shopping centers, and so on. Furthermore, collected information can provide indications about the most popular sights and hence services could be planned and provided accordingly. For example, an IoT sensor can detect the location of a visitor standing in front of a certain item in a museum, and then the information relevant to that item can be forwarded directly to the visitor's smart phone using an appropriate communication technology. Then, the frequency of visitors and the duration of their stay in front of that item could be transferred to a central server for future processing and analysis. This would lead to determining the most popular items, and will provide useful information for planning a smooth flow of tourists across the museum (to avoid congestion in certain areas, etc.).

In addition, with information tracked via MCS, smart loyalty and incentive programs can be devised, where a universal platform for loyalty and rewards can be applied through blockchain technology for example, enabling tourists to collect points and redeem rewards across a given country or region for sites and attractions they visit, thus promoting tourism activity [147].

G. SPORTS

Crowdsensing allows for crowd management through context-aware and location-aware services. In fact, these techniques allow tracking spectators in stadiums for safety purposes and also for providing contextual information that can enhance their experience. For example, a wireless sensor network implementing IoT technology could be used to manage the number of spectators in a football field. The system could be used to balance the seating of participants in different parts of the stadium. It could also be used to point them to the most suitable exit route in case of an emergency. Similarly to the Tourism case, smart loyalty and incentive programs can be devised, where a universal platform for loyalty and rewards can be applied through blockchain technology, enabling sports fans to collect points and redeem rewards for visits to stadiums to support their favorite football team for example.

Besides enhancing the experience for spectators, MCS could be used to encourage commitment to sports activities on the personal level. Indeed, as per the discussion in Sections 4.1 and 4.2, several devices such as fitness watches, BAN sensors, and a multitude of wearable devices are available in the market. They allow a person to track his/her exercise level, effort done, progress made, calories burned, miles walked, etc. They are based on IoT technologies

TABLE 6. Summary of the role of MCS in different applications.

Application	Role of MCS
A. HEALTHCARE	MCS allows the transfer of collected personal mHealth information to the cloud.
B. ENVIRONMENTAL	MCS enables an integrated air quality-monitoring network targeting improved urban life quality. This knowledge can then be used to prevent pollution or mitigate its effects.
C. SMART CITY	In a smart city, people can enhance their quality of life through participatory sensing and MCS.
D. INFRASTRUCTURE Drive Sensing	MCS is utilized for participatory sensing/crowdsensing/drive sensing scenarios where users willingly enable data collection.
D. INFRASTRUCTURE SHM	MCS allows complementing the role of traditional WSNs in SHM by using sensors in the drivers' smartphones to monitor the structural health of bridges.
E. SOCIAL NETWORKING	The MCS application collects data about personal activities and sends it to the remote server.
F. TOURISM	MCS help promote tourism activities [149].
G. SPORTS	Using MCS to promote sports and also to analyze the fitness level of the population.
H. PUBLIC SAFETY AND MILITARY APPLICATIONS	MCS helps in guiding the rescue efforts.

with data analytics, coupled with mobile applications. An interesting novel approach that could expand these activities using MCS, is to transfer this collected information to a centralized cloud, and use big data, cloud computing, and data analytics on a collective level to study the population's fitness level, and encourage commitment to personal health through exercising. This information could also be used in conjunction with the health data collected through the use of MCS in the healthcare sector as discussed previously. This would allow a detailed study of the correlation between sports activities and certain illnesses, and could guide certain awareness campaigns targeting a specific region or a specific age range of the population.

H. PUBLIC SAFETY AND MILITARY APPLICATIONS

MCS, coupled with advanced communications and cybersecurity could allow reliable information transfer between public safety teams or between military troops, in addition to securing communications between a command center and the military forces deployed on the field or the public safety teams deployed at an incident's location. In fact, new communications technologies designed for tactical use are affecting the battlefield with game-changing capabilities. Such technologies include Command, Control, Communications, Computers and Intelligence (C4I) technologies such as mobile and wireless networking, advanced antenna systems, jamming/anti-jamming capabilities, and software defined radios, among others [148].

With MCS, IoT and cybersecurity, reliable information can be collected from the field in real time and appropriate action can be taken as needed. BAN sensors could provide information about the health conditions of individual firefighters on a fire scene, or of soldiers in a battlefield. Important aspects to take into account are reducing energy consumption of BAN sensors (to increase their longevity in harsh battlefield conditions) and enhancing the efficiency of ad-hoc network formation and communication (to reduce overhead and communication time) when sensors and low power devices are involved.

In addition, the above techniques can be extended to a scenario with ground-to-air or air-to-ground communications. In fact, Flying Ad-Hoc Networks (FANETs) are becoming an integral part of public safety and of tactical networks. They consist of networks of drones or unmanned aerial vehicles (UAVs) [149]. In addition to their role in military communications, FANETs can have an important role in public safety applications such as maintaining security, border surveillance, etc. They can be used to remotely monitor large areas and transmit surveillance videos and various sensor measurement data in real-time (e.g. pollution levels after the explosion of a chemical plant), thus saving time and resources while increasing the efficiency of the security surveillance and monitoring system.

In the aforementioned discussion, the term ''MCS'' in the context of military and public safety scenarios is used with a slight abuse of the terminology. In fact, conversely to a ''normal'' MCS scenario where users are free to make the decision to participate or not, soldiers or public safety personnel *must* participate in real-time data collection/tranmission as this is the best way to ensure the most efficient operation of their unit and to ensure maximum protection for their lives. Nevertheless, the ''usual'' MCS can be used by civilian citizens in a public safety scenario to complement the measurement data sent by the public safety teams. For example, using MCS for sending the carbon dioxyde exposure levels caused by a fire, chemical exposure due a chemical plant incident, localization information afer an earthquake, etc., will provide valuable information to the authorities about the impact of these incidents on the affected population and will signifiantly help in guiding the rescue efforts. A summary of the role of MCS in different applications is given in Table 6.

V. DISCUSSION, CHALLENGES AND OPEN RESEARCH ISSUES

Mobile crowd-sensing plays a key role in future smart cities. Two fundamental areas that have a significant impact are energy conservation and security. The main challenges in MCS are hardware cost, system architecture, wireless connectivity, programmability, and security. The current **hardware cost** of smartphones capable of tracking human mobility and location is moderately high. Their **system architecture** is capable supporting several applications on top of it.

However, most of the applications and research examples are vertically integrated to maximize performance. Although MCS has great potential and offers many opportunities as mentioned above, it also has several challenges. The main challenges and open research issues facing MCS are the following:

A. USERS PARTICIPATION

Mobile crowd-sensing research has many challenges that need to be considered before deploying such systems on a large scale. One of these research challenges is finding an appropriate incentive mechanism that encourage users to participate in such system. One of the main challenges facing MCS is the availability of an adequate number of participants for the required application. The requirement can be also expressed in terms of participant geographical distribution. Therefore, incentive strategies, such as monetary or credit rewards, can be employed to increase the users' participation in MCS [150]. Minimizing the effect of running these applications on the performance of the smartphones (Minimizing the energy consumption, processing needs and network requirements) is also important to maintain the users' interest in the participation in MCS. The user participation becomes even more challenging in active participation since it requires more user's involvement. The research work in [151] discusses the barriers and shows that people are most likely to help when a minimum effort is required at no additional cost.

B. PRIVACY AND SECURITY

Another research challenge in MCS is the authenticity and integrity of the data collected from different users participating in the system. Privacy and security are very important in MCS applications that collect data related to the participant. It can be categorized into two types, user security and system security. From the system point of view, authentication and integrity verification of the information provided is critical, as this information will lead to decision making, which, if wrong, could have negative impact on the whole sensing platform. From the user point of view, this information is also critical as it may affect the user's privacy. Hence, it remains secure at the back-end processor. Each one of the above challenges could be a starting point for future research. In the following we provide some examples of existing approaches addressing both categories.

Due to human involvement, MCS brings some concerns about the privacy of the user using the mobile phone as well as the people surrounding the user. Thus, data privacy mechanisms are needed at the mobile devices, the network, and the remote server to protect private data such as users' location, vital signs, images …etc. For example, GPS sensor readings are utilized to have private information about the participant, such as daily movements as well as home and work locations. The collected GPS sensor data is shared within the community and can be used in a given city to obtain traffic congestion levels. Hence, it is very important to protect or maintain the participant privacy by not sharing his sensitive information [5], [105] while still enabling MCS applications.

To preserve privacy, anonymization is a technique to protect and secure the user's personal data, which seeks to secure the sensitive data and identity of record owners. It is the process of either removing or encrypting the information between participants and other parts to achieve the privacy and remain anonymous. Nonetheless, without the support of policies, processes, and people, the implementation of only data anonymization will be insufficient. Some companies fairly managed to implement data anonymization on a small scale using SQL scripts efficiently to encrypt data [152]. Some other companies have failed after obtaining the best data-masking tool [153]. Anonymization consists of techniques and procedures for data processing, algorithms, keys, and data life cycle. For privacy reasons, personal identifiable information (PII) needs to be anonymous for testing and analysis. There are several anonymization techniques such as 1) Generalization, which replaces the date of birth with reduced data size, such as the year of birth only, 2) Replacement such as using an alternative identification number, 3) Perturbation, introducing random changes to the data, 4) Suppression, which deletes from the released data partially or completely. However, these techniques can be applied only on at-rest or visible data i.e. logs, data exports, web pages [152], [153].

When malicious participants contribute with inaccurate sensor data (e.g., fake GPS readings), this could affect the integrity of the data collected from the system, which is a serious problem that could lead to lack of trust in the MCS application. Some researchers have worked on developing new approaches to resolve this problem. Some of these approaches depend on co-located infrastructure, while others depend on participation from the fixed expensive infrastructure, which could be expensive and not available sometimes. Another approach is based on trusted sensor hardware (sign) on a mobile device. These approaches need to be addressed to make sure that the integrity of the sensor data generated by the participants is reliable to provide significant decisions from the aggregate sensor data [43], [84], [105], [114]. Trust-based scores can be used and updated dynamically in order to quantify the trust level of each participant in MCS and thus deal with malicious participants (or simply participants sending erroneous measurements due to some sensor defect). Several reputation and trustworthiness metrics could be investigated [154]. Furthermore, distributed or localized trust management can be performed to reduce the load on the central server. For example, in [155], crowd-sensing in a vehicular ad hoc network (VANET) is studied, and the platoon head vehicle pre-processes the measurements from platoon members based on trust scores before forwarding the trustworthy ones to the server.

C. DATA SIZE

Big data techniques and data analytics algorithms can be used to effectively manage the huge amount and variety

TABLE 7. Summary of challenges realted to MCS and their diffrences/similarities with IoT challenges.

Challenge Area	MCS versus IoT
A. USERS PARTICIPATION	Both MCS and IoT applications motivate users' participation in many applications through incentive strategies.
B. PRIVACY AND SECURITY	Although this challenge is shared between IoT and MCS, the bulk of this challenge in MCS is concerning anonymization and privacy, while the challenge of trust is shared between the two areas.
C. DATA SIZE	Data size is a challenge that is common to IoT and MCS. Mobile devices and smartphones having data traffic split over different available wireless networks presents a major challenge. With MCS, an additional challenge is the generation of unexpected data due to human participation (as opposed to sensor data in IoT).
D. DATA ACCURACY	Data accuracy is a challenge that is common to IoT and MCS. However, MCS faces additional challenges, such as the compromise of data accuracy by malicious users and less control over the type of used devices.
E. OTHER CHALLENGES	Battery consumption and several other uncategorized challenges constitute a mixture of IoT/MCS challenges.

of sensed data [136]. Many applications may need to run analytical aggregation at the backend to detect patterns in the sensor data from various mobile devices. These patterns denote the features and characteristics of the events or the surrounding environment that are of interest to the user. These patterns may occur over some spatial scale and within some duration. For example, participants can report problems in public work facilities such as broken water pipes and defective traffic lights. The maintenance crew need to know the severity of the incident, and they can use this information to help rank and identify priorities and schedule repairs.

The large scale of MCS results in a large amount of data traffic that may overwhelm the network. In fact, conversely to networks based on IoT with purely automated sensor transmissions, MCS, due to the human participation, can sometimes generate unexpected traffic. Therefore, some techniques need to be employed to reduce the amount of traffic. This can be achieved by selecting certain users for sending sensed data, local data aggregation and processing at mobile devices and smartphones and having data traffic split over different available wireless networks (e.g., WiFi, Bluetooth, 3G, and LTE).

D. DATA ACCURACY

Although increasing the amount of collected data improves the accuracy of the monitored phenomenon or detected event, collecting sensed data from a large number of users may overload the communication network and remote servers. Therefore, it is required to determine clear and accurate relationships describing the dependence of the performance metric of MCS on the size of the collected data. Then, these dependencies and tradeoffs should be carefully considered to balance between the data accuracy from one side and the overloading of the communication network and servers on the other side.

Mobile devices and smartphones are equipped with different types of sensors from different manufacturers that may vary significantly in their sensitivity and noise immunity. Thus, there is a need to improve the data accuracy by identifying devices that are likely to produce accurate sensing data, performing global centralized data aggregation, and taking into consideration the spatiotemporal mobility patterns of the users of the mobile devices and smartphones [114], [127].

Although this challenge is common to both MCS and more "traditional" IoT networks, MCS faces additional issues. For example, accuracy in MCS can be compromised intentionally by malicious users. This issue was discussed in the paragraph related to trust in MCS in Section V.B. Another problem is that with MCS, there is less control on the type of used devices, and thus an increased degree of variety of devices is to be expected compared to IoT. This challenge is discussed in the previous paragraph.

E. OTHER CHALLENGES

Wireless connectivity indoors is still unpredictable using low-energy consumption radio frequency transceivers, particularly due to interference from electromagnetic fields produced by elevators, cordless phones at home, machinery, and computers among others. Another challenge is the programmability and re-programmability (re-configuration) necessary for energy conservation and node-to-node communication.

Researchers in [27], [151], and [156] are still faced with major obstacles to widely perform experiments, in spite of the huge demand for MCS applications for smartphones. These obstacles include the 1) the time and energy costs of resolving a robust, scalable, and visually attractive application and infrastructure, 2) the limited retention of users after using the applications for few weeks, and finally 3) human related issues such as privacy, incentives, and quality of data. Although, the idea of scaling to millions of devices is attractive, the widespread computing community still relies on expensive and short-term user contribution with small numbers of users. The work in [156] discussed a business-to-business model to limit the effect of obstacles facing mobile crowd-sensing. In [27] the battery size was shown to be the main factor limiting the use of mobile phones. Although energy consumption is a limiting factor in WSNs in general, an additional factor in MCS consists of the human user decision: Some users tend to refrain from participation in order to save battery energy. The challenges related to MCS are summarized in Table 7.

VI. CONCLUSION

Mobile crowd-sensing is an evolving topic with an extensive variety of possible applications. However, the outcome of MCS depends on the participation of people who might be concerned about their confidentiality. In particular, task management, as a central component of the crowd-sensing structure, poses several threats to participant privacy that need to be identified and addressed. In this survey, the MCS paradigm was reviewed for both participatory and opportunistic sensory. An overview of the MCS system architecture was provided, which includes several levels: crowd-sensing, data transmission, data collection, and applications. There is also a discussion about the challenges in terms of the number of applications in the market, the cost of mobile device, and we presented one of the topics that limits its use, namely the user retention. Some of the MCS architecture elements have been discussed, including data collection, communication media, data aggregation/fusion, as well as feature extraction and classification. The review also covers the main MCS applications such as environmental, infrastructure, and social. Some mobile crowd-sensing challenges have been discussed, such as user participation, privacy and security, data size, and data accuracy.

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