Mobile Crowdsourcing in Smart Cities: Technologies, Applications, and Future Challenges

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***Abstract*—Local administrations and governments aim at leveraging wireless communications and Internet of Things (IoT) technologies to manage the city infrastructures and enhance the public services in an efficient and sustainable manner. Furthermore, they strive to adopt smart and cost-effective mobile applications to deal with major urbanization problems, such as natural disasters, pollution, and traffic congestion. Mobile crowdsourcing (MCS) is known as a key emerging paradigm for enabling smart cities, which integrates the wisdom of dynamic crowds with mobile devices to provide decentralized ubiquitous services and applications. Using MCS solutions, residents (i.e., mobile carriers) play the role of active workers who generate a wealth of crowdsourced data to significantly promote the development of smart cities. In this paper, we present an overview of state-of-the-art technologies and applications of MCS in smart cities. First, we provide an overview of MCS in smart cities and highlight its major characteristics. Second, we introduce the general architecture of MCS and its enabling technologies. Third, we study novel applications of MCS in smart cities. Finally, we discuss several open problems and future research challenges in the context of MCS in smart cities.**

***Index Terms*—Cooperative computing, incentive mechanisms, Internet of Things (IoT), mobile crowdsourcing (MCS), mobility, resource sharing, smart cities, task scheduling.**

I. Introduction

URBANIZATION has been growing rapidly mainly due to the significant development of social productivity and the advances in science and technology [1]. The emergence of smart cities paves the way to improve the quality-of-life of people and public services in urban environments. In addition, it deals with the potential damages of over-rapid urbanization, such as environmental pollution [2], traffic congestion [3], and management chaos [4], [5]. The notion of smart city is originated from the concept of "smart planet" proposed by IBM in 2008 [6]. As defined by Batty, a smart city is "*a city in which Information and Communication Technology (ICT) are merged with traditional infrastructures, coordinated and integrated using new digital technologies*" [7]. The formation of smart cities is inseparable from two factors. First, representative ICT techniques, such as big data mining [8], Internet of Things (IoT) [9], mobile Internet [10], and cloud technologies [11] widely embedded in urban development that makes significant contributions to the construction of smart cities [12]. Second, the popularization of ICTs has promoted the tendency of innovation to be service-oriented and people-oriented, which leads to the adoption of increasing user-centric applications.

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Crowdsourcing is an effective technique that incorporate human intelligence to collect disparate sensing data in pervasive environments. In 2006, Howe [13] proposed the concept of crowdsourcing, which turns the role of individuals in smart cities from passive consumers into working consumers who act as service providers. Traditional crowdsourcing mechanisms mainly relied on the fixed Internet and infrastructure sensors (e.g., Wikipedia [14] and Amazon Mechanical Turk [15]), which are either centralized or static. In contrast, mobile crowdsourcing (MCS) combines the advantages of traditional ICT and novel mobile communications to provide cost efficient and high-quality services to different fields in pervasive environments. In particular, the mobility of individuals and cooperative communication and processing among portable devices (e.g., smartphones) in service delivery, as well as the recent advancements in wireless and mobile technologies (e.g., low latency and high-data-rate Internet access, mobile multimedia transmission, and mobile file sharing) [16]. The main characteristics of MCS can be featured as follows.

1) *Mobility:* Smart devices mirror the mobility patterns and social interactions of their carriers. Thus, the mobility information of devices can be utilized to improve the performance of MCS.
2) *Collaboration:* MCS enables decomposing and distributing tasks to eligible workers in a work crowd [17]. In this way, the crowd workers can collaboratively perform a set of partitioned tasks to achieve a global objective [18].
3) *Human Capacity:* Mobile individuals or workers play the role of data consumer and producer in MCS where their sensing, communication, and processing capacities are utilized to enhance the performance of MCS systems [19].

Taking the above characteristics into account, MCS can be defined as follows. MCS leverages device mobility and sensing

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capabilities, as well as human collaboration and intelligence to distributively perform tasks and provide cost-efficient applications and services.

The user mobility plays a key role on different aspects of MCS, especially in data sensing and collection. In particular, MCS utilizes the human-associated capabilities of mobile devices (e.g., human perception, knowledge, and experience) to streamline the performance of service delivery while reducing the resource consumption [19], [20]. The capabilities of MCS have been realized since mobile devices are equipped with various types of sensors, such as cameras, microphones, global positioning system (GPS), accelerometers, temperature, light, and health-monitoring sensors. In some scenarios, wireless access technologies and connectivity adapters (e.g., 4G cellular and WiFi) are considered as sensors to achieve positioning [21]. In addition to data sensing, MCS significantly expands the scope of data collection. In comparison to static crowdsourcing and centralized coordination, MCS can dynamically determine which individual workers participate in data collection processing tasks. Such flexibility provides an unprecedented opportunity to extend MCS to extensive application domains, such as image recognition, traffic monitoring, and environmental monitoring [22]–[24].

MCS can significantly strengthen the relations between residents and the government, as well as promote the evolution of smart cities. First, the residents can enhance their quality-of-life through various applications of MCS, such as in-building navigation [25], real-time public transportation [26], and commodity price comparison [27]. Second, residents can indirectly participate in urban management and planning activities. For instance, they can cooperate with local administrators and policy makers in public activities, such as reporting damages to public facilities [28], [29] and evaluating municipal services [30]. Third, the government departments can use MCS as a useful tool to monitor, manage, and upgrade the city infrastructures efficiently [31]. For example, a transportation department could manage and maintain the transportation system of a city by utilizing GPS data captured from smart cars [32].

TABLE I
SUMMARY OF PRIOR TUTORIAL/SURVEY ARTICLES

Reference	**Major contributions/field**
Chatzimilioudis *et al.* [16]	A taxonomy of crowdsourcing techniques and its applications
Gharaibeh *et al.* [39]	Achievements in various aspects of smart cities, the lessons learned, and research challenges
Phuttharak *et al.* [35]	MCS architectures and key development and implementation features
Ma *et al.* [36]	Opportunities and challenges in mobile crowd sensing brought on by human involvement.
Pan *et al.* [37]	Crowdsourcing in three different contexts: academics, enterprise, and social values
Faggiani *et al.* [38]	Smartphone-based MCS and an experimental MCS case study
Ganti *et al.* [33]	A categorization of MCS applications and their characteristics
Chittilappilly *et al.* [34]	General-purpose crowdsourcing classified into: incentive design, task assignment, and quality control
Kanhere *et al.* [27]	Participatory sensing in urban scenarios
Yang *et al.* [40]	Incentive mechanisms in crowdsourcer-centric and user-centric systems
Guo *et al.* [41]	Main components and applications of mobile crowd sensing and computing
Thomas *et al.* [43]	Application of crowdsourcing, the notion of smarter cities, and a four-quadrant model for crowdsourcing
Franco *et al.* [44]	Pervasive and crowdsourcing-enabled computing in urban environments
Feng *et al.* [42]	Security, privacy and trust in MCS
Yang *et al.* [19]	General architecture for MCS and challenges about security and privacy

A. Relevant Survey/Tutorial Articles

In the past few years, a number of existing works have discussed some aspects of MCS. Some studies explored the architectures, techniques, and applications of MCS. Chatzimilioudis *et al.* [16] provided a classification for major techniques in MCS and introduced some real-world application of MCS in location-based systems. Similarly, Ganti *et al.* [33] and Chittilappilly *et al.* [34] reviewed MCS technologies and highlighted their main characteristics. Phuttharak and Loke [35] studied the architectures of MCS and explored their implementation and development requirements. A general architecture for MCS networks is proposed with respect to data sensing and computing features [19]. Ma *et al.* [36] divided MCS into participatory and opportunistic methods and explored the opportunistic characteristics of human mobility from the perspectives of both sensing and transmission. In addition, Pan and Blevis [37] classified MCS by its drivers and oriented things. Faggiani *et al.* [38] investigated the role of network dynamics, data validity, and energy limitation in crowdsourcing. MCS in smart cities meets new challenges and opportunities, such as in terms of data management and security [39]. Kanhere [27] introduced participating crowdsourcing in which mobile carriers (e.g., taxi drivers) in urban scenarios collect different types of data streams from their environment and share them with each other through existing communication infrastructures (e.g., cellular networks or Wi-Fi access points). Yang *et al.* [40] designed incentive mechanisms to stimulate mobile users to participate in crowdsourcing activities. Guo *et al.* [41] extended the vision of participatory sensing to the integration of machine and human intelligence. Furthermore, Yang *et al.* [19] and Feng *et al.* [42] explored the security, trust, and privacy challenges in MCS. Table I summarizes the contributions of prior survey articles.

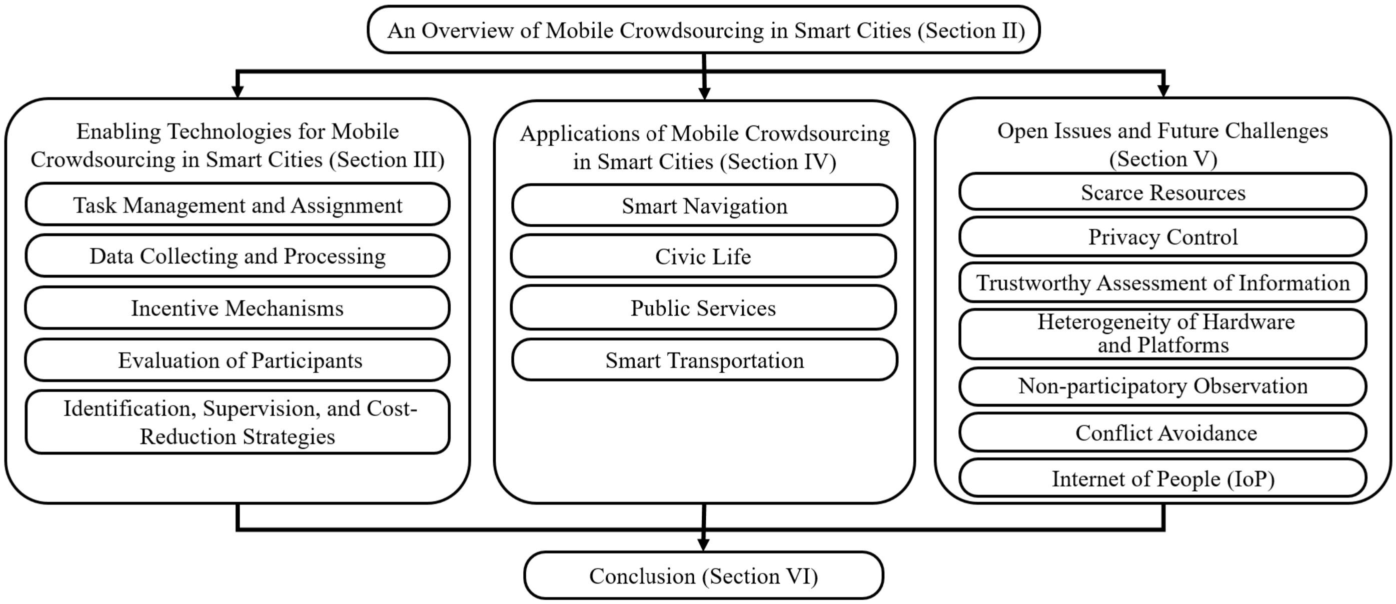

Fig. 1. Organization of the remaining parts of this paper.

B. Motivation and Contributions

Although the survey articles we introduced in Section I-A have studied some aspects of MCS (e.g., architectures, application, and incentive mechanisms), the role of MCS in smart cities is overlooked. Thus, the main objective of this paper is to fill the gap and address the characteristics of MCS in smart cities. To the best of our knowledge, this is the first survey article that provides an in-depth overview of MCS technologies and applications in smart cities. The main contributions of this paper can be summarized as follows.

1) We characterize the key components of MCS and introduce its capabilities in the context of smart cities.
2) We categorize enabling technologies of MCS in smart cities and identify their functions.
3) We survey the diverse applications of MCS in smart cities.
4) We discuss the key challenges of MCS in smart cities and highlight possible future research directions.

C. Research Methodology

The goal of this survey article is to study the major challenges of MCS in smart cities. The main target audience of this paper are researchers and practitioners from urban management, telecommunication, network science, computer science, and data science. The topics we study in Sections II–V are closely relevant to each other. In Section II, we first provide an overview of MCS in smart cities and characterize its main components. Next, we compare MCS with traditional crowdsourcing. Finally, we introduce the main features, advantages, and challenges of MCS in smart cities. In Section III, we explore enabling technologies of MCS in smart cities. First, we discuss the characteristics of MCS tasks and propose a categorization. Next, we introduce task assignment and allocation strategies. In particular, we explore data collecting and processing methods, including data quality improvement, preprocessing, and data evaluate. Furthermore, we study incentive mechanisms in four classes (i.e., monetary, entertainment-based, service-based, and social responsibility-based). In addition, we introduce several novel MCS technologies, such as identification, supervision, and expenditure reduction technologies. In Section IV, we introduce various applications of MCS and discuss its important role in smart cities. We categorize MCS applications into three classes (location, public and living, and traffic management and planning applications). We summarize the major contributions and specialties of the works we studied in Sections III and IV in Tables I–V. In Section V, we discuss representative visions and challenges of MCS in smart cities from both theoretical and application perspectives. The organization of the remaining parts of this paper is shown in Fig. 1.

II. Overview of MCS in Smart Cities

In this section, we first introduce a general framework for MCS systems. Next, we summarize the typical classifications of MCS. Finally, we outline the main features, advantages, and challenges of MCS in smart cities.

A. Framework of Mobile Crowdsourcing

In this part, we present the general framework of MCS systems including its architecture and main components.

1) Architecture of MCS Systems: Various MCS architecture models have been proposed in [45] and [46]. In this section, we introduce the most common architectures.

Fig. 2 illustrates the general architectures of MCS, as well as its participating entities. The architecture consists of several entities, including service providers, end-users, and working crowds [24]. A service provider is generally a platform that handles tasks and provides crowdsourcing services

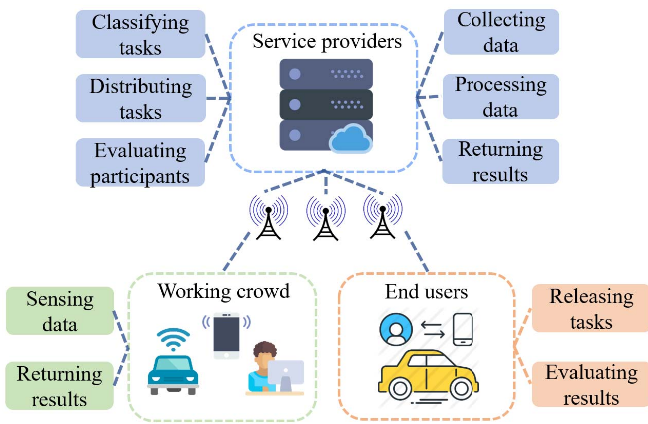

Fig. 2. Main entities and functions of a general MCS system in smart cities.

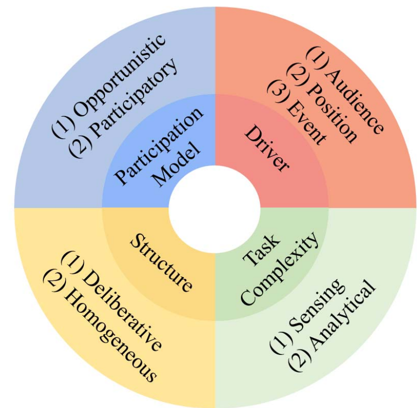

Fig. 3. Classification of MCS systems.

to end-users. In the context of smart cities, end-users are generally pedestrians with their carried mobile devices or connected vehicles that publish one or multiple tasks. The service provider allocates the received tasks to appropriate working crowds. A task can be completed by a worker using its smart vehicles, mobile devices (such as camera, smartphone, or smart watch), laptops, etc. Some studies regard an end-user and a working individual as an entity, which is called "participant." Yang *et al.* [19] divided the working crowds into sensing crowds and computing crowds. Korthaus and Dai [47] proposed an architecture, which includes a highly integrated server provider called *task management component*. The main functions in their proposed architecture are managing tasks, system environment, and user profiles. The highly integrated architecture enhances the connection between the components and improve their efficiency.

2) Main Functions: Fig. 2 shows the main functions of the service providers, end-users, and working crowds in an MCS system. Once a request from an end-user is received, the service provider classifies the tasks and divides them into small pieces. Then, it distributes the small tasks to interested workers and waits to receive the tasks' outcomes. After receiving all results, the platform processes the data and returns the final results to end-users, so that crowdsourcing tasks are completed. After finishing several tasks, service provider will evaluate the participants to judge whether their behavior is honest or not. End-users can also evaluate results and submit their suggestions to the platform.

B. Classification of MCS Systems

Different types of MCS systems have been proposed in the literature. We identify the common types of MCS systems in Fig. 3 and explain their properties as follows.

1) Participatory Forms: In general, mobile workers get involved in MCS activities in two forms [36].

1) *Opportunistic:* A worker in this approach receives the data directly from sensors on its mobile device seamlessly. Workers are unconscious about the process of data collecting. The sensors automatically capture the position, moving image, or other data [48].
2) *Participatory:* A worker deliberately submits data to the system by using the applications on its mobile devices. The time, location, and the method of data collection is identified by the worker consciously. The participatory method is carried out the same as the traditional Web-based systems.

2) Drivers: Generally, MCS systems are divided into audience-driven, location-driven, and event-driven systems. We explain the properties of each type as follows.

1) *Audience-Driven:* Participators in audience-driven systems are at the center of the crowdsourcing system. For example, Twitter can be used as a digital back-channel at the technology-oriented conferences.
2) *Location-Driven:* Location-driven MCS focuses on a particular place. For example, Kettemann *et al.* [49] designed a location-driven application for public facility management that provides public facilities in a particular place.
3) *Event-Driven:* In contrast to the audience-driven, this class of MCS systems take an event as the core, where a crowd is recruited for a particular event with a start and end tags. A representative example in this category is the IBM's Innovation Jam offering platform,[1] which is an online system involving thousands of people brainstorming a set of problems.

3) Task Complexity: We classify MCS tasks into sensing and analytical tasks, which can be described as follows.

1) *Sensing:* Sensing tasks refer to automatic sensing that can be performed by workers through the sensors embedded on their mobile devices. For example, a noise in an environment can be detected by the microphones on mobile devices [50].
2) *Analytical:* Analytical tasks need the participation of human intelligence. The tasks in this category (e.g., reviewing books or translating articles) require the recognition ability of workers to be analyzed.

4) Contribution Structure: The contribution of crowd individuals in MCS tasks can be evaluated in different ways. In some applications (e.g., collecting environment data or taking photographs from a certain place), the quality of contributions

[1] https://www.collaborationjam.com/

of workers is trivial and does not affect the MCS outcome significantly. By contrast, in other tasks (e.g., translating or marking photographs), the quality of tasks carried out by different workers is important and affects the final results considerably. From the quality perspective, MCS tasks can be divided into two types.

1) *Homogeneous:* Contributions submitted by different individuals have the same weight, and they are not evaluated separately.
2) *Heterogeneous:* Contributions submitted by different individuals have different weights and are evaluated individually. The weight of contributions makes it possible to compare them with each other and evaluate the performance of workers.

C. Features and Challenges of MCS Systems

In comparison with traditional crowdsourcing, MCS brings several unique features for efficient data sensing and collection. In the following, we characterizes key features and challenges in MCS.

1) *High Efficiency:* With the emergence of powerful mobile devices, the efficiency of MCS becomes much higher than the traditional crowdsourcing. In addition, most of the mobile devices are equipped with high-performance processors and multimodality sensing capabilities, which help gathering and processing data efficiently [33]. On the other hand, with the advent of advanced ICT, transmitting data in high rate enables real-time data collection and processing. Besides, people usually carry their devices wherever they go and whatever they do, which allows the tasks to be done pervasively. Moreover, sufficient works speed up the process of MCS and improve its efficiency.
2) *Accessibility and Portability:* Taking advantage of the popularity of mobile devices, a large number of users can participate in MCS applications. This is because a user (as a worker) only needs an ordinary mobile device to participate in crowdsourcing tasks. Besides, more and more applications support cloud storage, which makes the migration of user data easy. Users can transfer their information by logging in their accounts. The information can be transformed between different platforms or operating systems, which reflects the portability of MCS.
3) *Universal:* The development of MCS applications is relatively simple. Today, most of the mobile applications can be cross platform and have high compatibility. Moreover, they are always interface-friendly and easy to use [51]. Therefore, users who have no crowdsourcing experience can also benefit from the system. The universal characteristics of MCS applications make them attractive for new users.
4) *Widely Distributed:* Crowdsourcing users are generally distributed in large geographical areas. The type of data collected by MCS is diverse; and the data of workers from different countries and regions can be acquired easily. MCS platforms can push crowdsourcing tasks to interested users seamlessly [52]. In addition, human mobility in different regions has unique characteristics, such as spatio-temporal correlation, hotspots' effects, and sociality. These advantages are helpful for constructing accurate mobility models, which can significantly improve the sensing quality and the efficient of sensing strategies [36].
5) *Low Cost:* Compared with traditional sensor networks, MCS can help develop large-scale and low-cost sensing applications. For instance, traditional traffic information acquisition systems require installing sensors on roads, which is too costly. By contrast, traffic information in modern transpiration systems can be sensed by smart devices installed in smart cars [53].
6) *Dynamic User Groups:* The location and contextual situation of users in MCS applications can be changed constantly. Taking advantage of mobility, dynamic workers offer real-time data, which can helpful for on-demand tasks and applications. Nevertheless, the variation of user features can open major problems, especially in handling data. For instance, sensing data might be lost or not stored accurately.

Summary: An MCS system consists of service providers, end-users, and working crowds. The three entities collaborate with each other to complete the MCS tasks. MCS has different classification in different domains regarding the participatory method, drivers, task complexity, and contribution structure. MCS can be efficient and accessible in dynamic user groups but brings several management and coordination challenges.

III. Technologies of Task Scheduling, Data Processing, and Incentive Mechanism

In this section, we describe enabling technologies of MCS in smart cities. Fig. 4 illustrates a general process of MCS. When a service requester submits a task, the platform characterizes, classifies, and assigns the task to appropriate workers. In this step, different forms of incentive can be provided to the interested workers. Receiving the results, the platform evaluates the workers' performance to judge the data quality. Then, the platform processes the data and returns the results to service requesters. The service requesters may provide their comments, which can be transformed to the workers. The platform is also responsible for the resource control and quality supervision.

In general, the main components in a mature MCS system are: task management and assignment, data collection and processing, incentive mechanisms, evaluation of participants, and cost-reduction strategies. In the following, we explain the properties of each component.

A. Task Management and Assignment

Task management and assignment are the main components that affect the efficiency of MCS significantly [54], [55]. In this part, we summarize the characteristics of tasks, the process of task management and assignment, as well as their enabling technologies. Table II summarizes the main contributions and features of the work we study in this section.

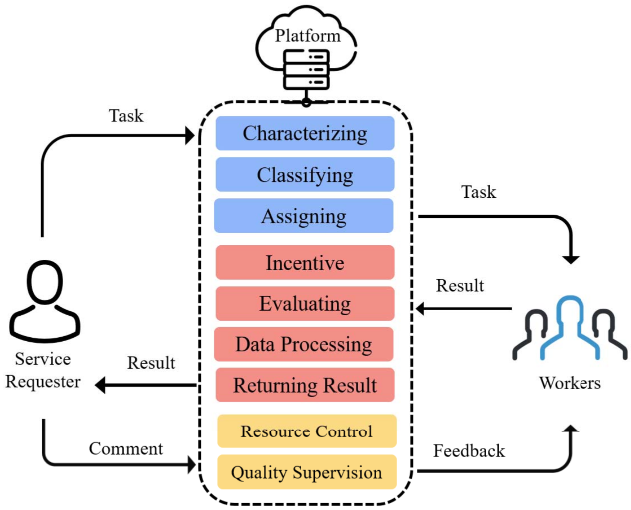

Fig. 4. General process of performing an MCS task.

1) Task Characteristics: Extracting the characteristics of tasks can help categorize them and speed up their assignment [56]. For the assignment and scheduling tasks, following factors should be considered.

1) *Task Feasibility:* Receiving a task, the crowdsourcing platform primarily needs to judge the feasibility of the task. To this aim, the platform evaluates whether the available resources can guarantee the completion of the task with the requested quality of service. A particular task may need different types of storage, computing, and power resources. Thus, the platform needs to evaluate whether the resources are sufficient under the premise of ensuring the quality. Once the feasibility of the task is validated, the platform aims to find an optimal solution for the task. Third, the platform considers whether the fund provided by the task publishers is sufficient. The crowdsourcing platform can accept or reject a task based on its revenues and costs.
2) *Completion Time:* The completion time of a task can be discussed from two perspectives. First, the platform checks whether the completion time of the task is in conflict with the sequence of current tasks in the system. Second, the platform considers the participating time of interested workers. The publishing time of a task has a significant impact on its completion time and efficiency [57]. Besides, the platform can select the appropriate equipment and crowd resources according to the duration of the task [24]. For example, it is reasonable to assign tasks with short completion time to users who normally use their mobile devices for a short time [58]. Vaish *et al.* [59] used the time of unlocking a smartphone to complete a simple task which effectively uses the spare time of users to complete tasks. Moreover, the number of workers, the amount of remaining resources, and the quality of data can vary over time [36]. Thus, the platform should measure the system changes. For example, allowing partial data to be submitted can prevent the data lose due to the device shutdown.
3) *Spacial Factors:* Spatial factors can greatly influence the accuracy of MCS and participants' privacy [75]. Therefore, the platform needs suitable management method that takes privacy into account while having high efficiency [61]. Spatial factors include two aspects.
   a) *Scope:* The scope refers to the area requested by tasks. According to the task requirements, the crowdsourcing platform determines the scope of MCS. The platform is able to select a range of areas, such as a country or even a business district for MCS.
   b) *Location:* Some MCS tasks only focus on events in a particular location. Workers can get accurate information when they arrive at the designated place.
4) *Task Complexity:* Tasks can be divided into sensing and analytical tasks. Tasks with different complexity can be solved by workers with different knowledge levels. The platform should assign appropriate workers to a task with respect to its complexity, which is helpful for effective resource usage.
5) *Task Pricing:* Task pricing determines the operating cost of a task based on the experience of workers and the rules designed by the platform. However, a pricing scheme may lack a dynamic mechanism and leans to an uneven pricing. To deal with unreasonable pricing, many scholars recommend to employ a bidding mechanism [62]–[64], [76]. An applicable biding algorithm should satisfy the economical properties, such as individual rationality and truthfulness. The bidding method effectively coordinates the profits of the platform and participants to promote their cooperation.
6) *Workers:* The platform generally describes a worker from several aspects, such as working time, location, age, gender, work, preference, and device type [58], [65], [77]. The basic factors a worker considers in performing MCS tasks are time, position, and preference, which are explained as follows.
   a) *Time:* The working time of participants in MCS activities can be coincide with their free time (e.g., their time after work) [57]. In this way, the performance of tasks performed by them can be significantly enhanced. For instance, assigning tasks to worker in their expected times can maximize the system profit.
   b) *Location:* Workers generally have to attend particular locations to perform their assigned tasks, which is often costly. Therefore, the location of workers affects the assignment and the cost of tasks. Thebault-Spieker *et al.* [78] find that the distance between workers and tasks has a significant impact on the willingness of workers the tasks completion cost. For instance, a long distance between a task and assigned workers decreases the workers' willingness to participate in the task and increases the task cost.
   c) *Preferences:* An MCS should consider the interests and preferences of workers in tasks allocation. For

TABLE II
SUMMARY OF THE TASK MANAGEMENT AND ASSIGNMENT TECHNOLOGIES

References	**Major contributions**	**Specialties**
Yang *et al.* [19]	Discussing several critical security and privacy challenges in MCS	Using an authentication technology to achieve both availability and reliability
Duan *et al.* [17]	A truthful auction mechanism to investigate task allocation and pricing	The mechanisms guarantee users bidding with truthful values
Shah *et al.* [18]	A truthful auction mechanism to maximize the profit of the MCS systems	The mechanism is computationally efficient (polynomial time complexity)
Gao *et al.* [60]	A floor reconstruction system that leverages sensing data from mobile users	Producing complete floor plans by combining traces and location
Rajan *et al.* [59]	Presenting twitch crowdsourcing that encourage short bursts of contributions	Lowering the threshold to participation in crowdsourcing
Yan *et al.* [61]	A task assignment method for privacy-aware spatial crowdsourcing	The method is efficient when tasks are geometric
Zhang *et al.* [62]	A MCS mechanism by eliminating dishonest behavior and discourages free-riding and false-reporting	The mechanism is computationally efficient and ensures balanced-budget
Wei *et al.* [63]	An online auction mechanism with four pricing plans	The auction model is strategy-proof, individual rational, and ensure budget balance
Wang emphet al. [64]	Presenting an auction model for quality-aware and fine-grained MCS	The mechanism achieves truthfulness, individual rationality and computational efficiency
Vaataja *et al.* [65]	Discussing the experiences and factors that affect the participation preferences	Using mobile assignments for crowdsourcing in a real-world field trial
Mashhadi *et al.* [66]	Technique that employes users' mobility pattern and contribution history to estimate their credibility	Estimating the quality of contributions based on the contributor's mobility, as well as their trustworthiness score
Huang *et al.* [67]	A reputation system for evaluating the trustworthiness of volunteer contributions in participatory sensing	The system outperforms the state-of-the-art reputation scheme by a factor of three
Bhattacharjee *et al.* [68]	A reputation model to segregate different user classes	The model captures differences in user behaviors by unifying both quality and quantity
Wang *et al.* [69]	Trustworthy crowdsourcing framework to discover services and resources	The framework detects unreliable crowdsourcing participants
Tong *et al.* [70]	Two-phase MCS framework	Verifying the efficiency, effectiveness and scalability
Han *et al.* [71]	An offline auction mechanism in MCS	The mechanisms achieve truthfulness and individual rationality
Hassani *et al.* [72]	Context-aware task allocation approach	Allocating sensing tasks to the best participants while improving energy efficiency
Wang *et al.* [73]	An incentive mechanism with privacy protection in MCS systems	The mechanism selects the candidate workers statically and identifies winners dynamically
Feng *et al.* [74]	Truthful auction mechanisms for different cases of MCS	The mechanism achieves truthfulness, individual rationality, and computational efficiency

example, the interest of workers in collecting photographs are very different [57], [65]. Thus, the platform should recommend tasks to workers based on their interests.

2) Task Recommendation and Assignment: Once the platform evaluates the participants, it recommends tasks to interested participants. We summarize task assignments and recommendation methods as follows.

1) *Assigning Subtasks:* Dividing decomposable tasks into multiple subtasks is a common method to achieve task synchronization and parallelization [79]. Thus, each subtask can be assigned to different workers. In this way, different subtasks from different tasks can be assigned to a particular worker [19], [64], [76]. This method reduces the budget and improves the crowdsourcing efficiency [70]. However, it requires a reasonable partitioning of tasks and trusted algorithms to aggregate data from multiple parties.
2) *Participation Information:* This method considers the characteristics of workers (such as acceptable time, locations, preferences, and skills) to assign tasks [71], [72]. The participation information method enables a task to be completed by an appropriate staff in a high quality [77], [80].

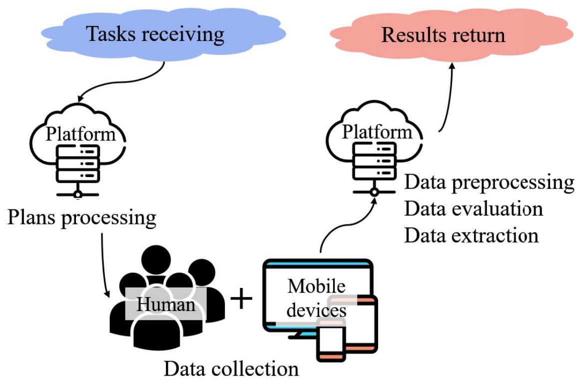

Fig. 5. Process of completing a data-driven task.

3) *Auction:* Auction is a common approach to allocate MCS tasks to interested workers efficiently while satisfying the economic properties. In particular, an auction mechanism is computationally efficient, as well as it can achieve rationality and truthfulness properties [40]. Using the auction approach, the platform plays the role of the auctioneer in the process [18]. Interested participants submit their bids to the platform. Next, the platform selects the winning participants by analyzing their bids [17]. However, due to the dynamic nature of MCS, common auction mechanisms may not be suitable for a dynamic MCS environment [73]. Feng *et al.* [74] brought the dynamics of devices and the randomness of tasks into consideration to relief the system dynamics.

B. Data Collecting and Processing

Data plays an important role in MCS in smart cities. Fig. 5 shows the process of completing a data-driven task. The platform develops a data plan after receiving a task. First, the data is preprocessed, evaluated, and its main features are extracted. Next, the platform allocates the task to appropriate workers. Finally, the results are delivered to the service requester. In the rest of this section, first, we analyze the source and type of data. Second, we address the common data processing technologies. Table III shows the main contributions and features of existing studies for data collection and processing.

MCS in smart cities relies on the support of big data technologies. The data is mainly captured through the sensors of mobile devices carried by participations [92]. On the one hand, the diversity of sensors promote the advance of smart cities and provide a wider range of data types for MCS. Modern mobile devices are equipped with rich sensors that have abundant functionalities. For example, the camera sensor can be used to capture images or record videos. The sound can be recorded using the audio sensor. The accelerometer and gyroscope can reflect individuals' state of motion. GPS data can capture the location information of users, as well as their moving tracks. Furthermore, future mobile devices may include pollution monitoring sensors [30]. At the same time, smart watches and smart bracelets contain healthy sensors that have the ability to measure the heart rate and body temperature of individuals. With the advance of smart cars, in addition to GPS and radar, cars will be equipped with light sensors, road condition sensors, and passenger physiological state sensors. Furthermore, smart cars will have powerful computing capacity and provide MCS data in the future [81], [93].

1) Data Quality: The quality of data significantly affect the performance of MCS. However, data captured by participants can be inevitably low quality and inaccurate. On the one hand, failures of networks or devices can lead to incomplete data. On the other hand, the quality of data provided by participants can be low due to different reasons. Detecting low-quality data is a challenging task. Besides, the data in MCS is gathered, which means it has characteristics of the group. The characteristics need to be considered in studies. For instance, Zhang *et al.* [94] proposed a novel algorithm to maximize the total coverage quality in a set of mobile users. Recently, some approaches have been proposed to improve the data quality submitted by participants. Hoh *et al.* [82] designed a trust-based parking information incentive system which punishes unreliable mobile user groups. Similarly, Jin *et al.* [83] considered the quality of data submitted by participants in the incentive mechanism. Gong *et al.* [84] designed a data protocol to calculate the real and required data via a semi-honest third party in the presence of malicious participants. In addition, Chen *et al.* [85] evaluated workers according to their historical contributions. In particular, they regulate the behavior of participants. Besides, simple baseline mechanism is used as first level filtering to monitor whether the participants' behavior meets the requirements. Incentive mechanism also be used in improving data quality. Song *et al.* [95] introduced the quality of sensing into incentive mechanisms and provide a higher valuation to the platform. Since the energy and sensing capabilities of mobile devices are limited, the data sensing framework should consider energy and budget constraints [96]. Therefore, effective incentive mechanisms should be designed to stimulate the cooperation of mobile participants.

2) Data Management and Processing: One of the main objectives in MCS is acquiring a large amount of data captured by mobile participants. A mass of mobile devices in smart cities can create a large volume of data. Thus, the efficient management and utilization of big data techniques in MCS services is a promising solution. However, there are several data privacy and security challenges, which restricts the development of smart cities [39]. Once data are collected, the platform aggregates and analyzes the data to complete the tasks and deliver services. In this part, we discuss data processing problems and techniques in an MCS system.

Designing a data middleware is a common strategy in MCS [97]. Following this strategy, passive sensing data submitted and participants' contributions are transmitted to a data middleware. After processing the data, the middleware provides personalized services to consumers. Bajaj *et al.* [86] developed middlewares that ensure the connectivity of crowdsourcing application. Pu *et al.* [87] proposed a framework that uses the Web for mobile computing. Users can use nearby devices to facilitate their calculation. Ning *et al.* [46] proposed a social-aware communication framework, which is helpful for the allocation of nearby devices.

TABLE III
SUMMARY OF DATA COLLECTING AND PROCESSING TECHNOLOGIES

References	Major contributions	Specialties
Motta *et al.* [30]	A framework to assess the maturity of crowdsourcing municipal services	A MCS system design based on existing social media platforms
Ning *et al.* [46]	A crowdsourcing research application to determine unique patterns for a variety of illnesses	The application can understand temperature variation between individuals
Kong *et al.* [81]	A procedure to generate social vehicular mobility dataset from floating car data	The mechanism has the advantage of wide universality
Hoh *et al.* [82]	An incentive mechanism in trustworthy crowdsourced parking systems	The active confirmation scheme validates the parking information utility using game-theoretic based incentive protocols
Jin *et al.* [83]	Incentive mechanisms based on reverse combinatorial auctions in MCS	The mechanism achieves a near-optimal social welfare with low time complexity
Gong *et al.* [84]	A flexible optimization framework to adjust any desired trade-off point	Numerical and experiments to show the effectiveness and efficiency of the proposed framework
Chen *et al.* [85]	Principles of efficiently harnessing MCS on a smart parking case study	Integrates the functionality of parking guidance into a road navigation system
Bajaj *et al.* [86]	Providing commuters with personalized routes with the most convenience	Using a middleware to enable a convenient transit by using crowdsourcing
Pu *et al.* [87]	Deriving an optimal worker recruitment policy in a dynamic programming principle	The paradigm is cost-efficient with low time complexity and energy consumption
Sherchan *et al.* [88]	A platform to support data collection for MCS	The platform supports delivering real-time information to mobile users for queries
Zhang *et al.* [89]	A participant coordination framework	The framework allows optimal QoI for sensing tasks without knowing trajectories
Bosse *et al.* [90]	Applying MCS in violence and criminality domain	Extending social machines to obtain semantics over social networks data
Karaliopoulos *et al.* [91]	A novel perspective on the payment distribution problem faced by MCS	Achieving good approximations of the optimal solutions and substantially outperforms

With the development of cloud computing technology, many scholars study the applications of cloud storage and computing in MCS [33], [88]. Using cloud computing can not only deal with large-scale MCS data but also reduce user's storage and computational pressure effectively. Assigning system components over the cloud can also analyze data of MCS and drive applications. Using cloud technology to manage and compute data makes it possible to integrate and process real-time data as well as social network data to support real-time queries [88]. Another advantage of cloud computing is the ability to filter data in the cloud. The cloud filtering mechanism improves the quality of the data involved in the MCS [89].

We divided the data processing into three phases: 1) data preprocessing; 2) data evaluation; and 3) data extraction, where the description of each phase is given as follows.

1) *Data Preprocessing:* The first step in data processing is to clean the data by eliminating outliers. The data collected by mobile devices can be invalid mainly because of the following reasons. First, data captured by sensors might be inaccurate because of the sensors' low sensing capability. Second, the network or equipment can fail which lead to incomplete data sensing. Third, the sensing data can be noisy and interfere with each other. Fourth, data duplication and redundancy problems can occur. Thus, data preprocessing can help remove redundant and incomplete data, improve the data quality, and ensure the subsequent computational efficiency.
2) *Data Evaluation:* Although data preprocessing aims at cleaning the data, it can barely discover false data submitted by malicious users. Data evaluation phase process the data deeply to detect and delete deceptive data. For instance, platforms design algorithms [90] can be applied to evaluate and delete unqualified data.
3) *Data Extraction:* Data extraction is performed after the data evaluation. Data aggregation is the basic technology in the process of data extraction. The platform extracts valuable information based on the users' requirement. Machine learning and data mining are common technologies to enhance the ability to extract information [91]. After data analysis and visualization, the system will return results to task requesters.

3) Cloud Computing: In this part, we give a brief introduction to data computing methods in MCS. The computing of large scale data collected by MCS sensors consumes great computing resources. Cloud Computing is an Internet-based computing approach in which shared hardware and software resources and information can be provided to computers and other devices on demand [98]. Cloud computing is a powerful technology to perform massive-scale and complex computing [99], which enables MCS to compute big data and return

TABLE IV
SUMMARY OF INCENTIVE MECHANISMS

References	**Major contributions**	**Specialties**
Yang *et al.* [40]	Incentive mechanisms in MCS to attract more participation	Efficient, individually rational, profitable, and truthful
Yan *et al.* [102]	Application which combines MCS and software testing	Supporting the testing of mobile application and web services
Yang *et al.* [103]	A social incentive mechanism	Stimulating the social ties of participants
Goncalves *et al.* [104]	Investigating altruistic use of interactive public displays settings as a MCS mechanism	Performance is improved by applying validation check mechanisms
Kulkarni *et al.* [105]	A marketplace model to achieve a robust and high-quality MCS system	Filtering workers and allowing the crowd to solve unfamiliar tasks
Feng *et al.* [106]	Stimulating smartphone users to join MCS activities	Achieving truthfulness, individual rationality and computationally efficiency
Zhang *et al.* [107]	Three online incentive mechanisms	Computational efficiency, individual rationality, and profitability
Liu *et al.* [108]	The gamification concept to improve user engagement in MCS	Achieving better engaging with end-users
Afridi *et al.* [109]	Dealing with the uncertainty and quality of social mobile computing systems	Optimizing the systems response, adapting the components and decreasing the uncertainty
Sun *et al.* [110]	A secure and privacy-preserving object-finding system through MCS	High efficacy and efficiency are confirmed by extensive simulations
Farkas *et al.* [111]	A framework to facilitate the development of crowd-assisted smart city applications	Event detection in traffic stops

results. With the increase of equipment type and quantity, MCS data quantity increases. Upload data to the cloud consumes a lot of network and energy resources. The results do not guarantee the real-time performance. Many scholars study mobile cloud computing to relieve the above problems. Mobile cloud computing is the infrastructure where data storage and data processing take place outside of mobile devices [100]. MCS uses mobile cloud computing to deliver real-time service with mobile devices that have computing and storage capabilities [101].

C. Incentive Mechanisms

To ensure the normal operation and performance of MCS, the platform should attract sufficient high-quality workers [112]. However, participants might be reluctant to participate in crowdsourcing tasks unless appropriate incentives are provided. In particular, participating in MCS activities consume different resources, such as transportation costs, equipment resources, and communication costs. Moreover, MCS tasks may require the participants' personal information, such as location, preference, and device type, which brings privacy and security challenges [113]. In addition, the quality of data collected by a participant can be relatively low if effective incentives are not provided, which can affect the quality of service of the platform negatively.

Different types of incentive mechanisms have been proposed in the literature. The incentives can be provided in forms of money, entertainment, mutual benefit principle, social contact, reputation, service, reputation, altruism, social responsibility, social psychology, and the joy of sharing knowledge [16], [102]–[104], [114]. MCS platforms can use one or more of these incentives. Here, we present a detailed description of commonly used incentive mechanisms in MCS systems. Table IV shows the main contributions and features of the works we study in this section.

1) Monetary Incentives: Monetary incentives are the most effective methods to motivate users to participate in MCS tasks. It compensates the workers' contributions and is easy to form MCS market [80], [105]. A straightforward monetary incentive approach is task pricing. In the process of pricing tasks, an auction mechanism can be applied to identify the participants of each task. The auction mechanism can not only set reasonable task prices and choose winners but also it can achieve individual rationality and truthfulness [40], [74].

Some existing works have studied the role of auction-based incentive mechanism in MCS. Feng *et al.* [106] used a near-optimal approximate algorithm for determining the winning bids with polynomial-time computation complexity. Wei *et al.* [63] designed a two-sided online auction mechanism to satisfy the balanced-budget property. Zhang *et al.* [107] proposed a flexible online incentive mechanism that has the potential to develop practical and large-scale MCS applications.

The main challenge in monetary incentives is the existence of dishonest users. A simple method to deal with this problem is using deposit. In this method, a certain amount of money is submitted by each participant as the security deposit, which can motivate participants to take part in activities based on the preferences of the platform. This approach requires the support of an evaluating technology to validate the contribution of the participants. If a participant acts honestly, the security deposit will be refunded; otherwise, the security deposit will be deducted [62]. In addition, incentive mechanisms can regulate the behavior of workers. Wang *et al.* [69] proposed a reputation-based auction mechanism which selects winners and identifies their payment by estimating their reliability. Some existing works have designed countermeasures to address the privacy of participants. For instance, Wang *et al.* [73] proposed the auction mechanism with protection of privacy.

2) Entertainment-Based Incentives: Adding entertainment incentives to MCS tasks can attract a lot of participants. A sample technique is to apply game models, based on which players can get pleasure in the game while submitting high-quality data. The incentive mechanism based on entertainment is mainly used in the following three scenarios.

1) *Image Analysis:* This scenario includes language recognition, image classification, image marking, and so on [108]. Some applications push pictures through games to stimulate participants. The worker's answer is acceptable when it is correct with most of the player's answers. Using game-based incentive methods, the information of images can be collected swiftly.
2) *Capturing Geographic Information:* Games that run on locatable devices can efficiently collect players' locations information. The collected information can help build detailed geography map. In addition, photographs collected by games can help to create panoramic maps.
3) *Network Facilities Detection:* It is possible to detect the coverage and signal strength of wireless networks in a region by using games to realize the state of network facilities. This information provides a certain reference for service providers to deliver their services.

The incentive mechanism based on entertainments has high requirements for superior applications. First of all, the players' novelty of the game decreases with time. Developers need to update frequently to attract users. Second, users may prohibit certain privacy rights of the game, which bring certain obstacles to data acquisition.

3) Service-Based Incentives: In some applications, workers receive services from the platform. Such applications can use the principle of mutual benefit to motivate their workers to get free services from the same platform [109]. Chen *et al.* [85] designed a smart parking system based on mutual benefit. The authors find that a modest contribution among the participants could attract more participants and promote MCS. Yan *et al.* [121] proposed a novel parking reservation system in which users can reserve free parking lot. If a buyer successfully stops at a predetermined location truthfully, he can resell the site through the system and get benefits.

4) Social Responsibility-Based Incentives: Socially responsible citizens are willing to consciously contribute to the society. Social responsibility-based incentives effectively promote the development of public service in smart cities by using citizen's sense of responsibility. Thus, service applications can collect data from people with altruism and dedication free of charge. Goncalves *et al.* [104] demonstrated the feasibility of altruism, for example, by providing information to help others discover people or objects [110]. Based on the responsibility-based incentives, public sectors and government applications can collect urban information from the public. In return, citizens can give feedback on urban infrastructure, transportation, and environment, which helps the construction of smart cities and the improvement of people's living standards [111].

D. Evaluation of Participants

Evaluating participants in MCS activities can improve the quality of MCS services. If the platform labels the participants based on their performance, it can estimate their reliability in tasks assignment. As a result, the platform can provide individual tasks for workers based on their reliability [122].

1) Evaluating Methods: There are several methods to evaluate the performance of participants. The common approach is to estimate the credibility of participants by evaluating the quality of their historical contributions [66]. Some scholars establish a reputation system to assess the performance of participants [67], [68]. Wang *et al.* [69] proposed a method that distributes tasks to participants by evaluating their reliability. In addition, machine learning technique can be designed to identify and quantify the set of skills needed for constructing a over-time model. This method facilitates the interactions between the platform and employees, which can significantly improve the workers' skills and speed up the task allocation.

2) Reputation Mechanism: Some scholars have developed reputation management program to evaluate the credibility and cost performance of mobile users to select participants. The analysis and simulations demonstrate the mechanism's improvement [123]. At the same time, some platforms suffer from low-quality work while the participants have high reputation scores. A reputation system should have feedback algorithm to rebound the consequences [124], [125].

E. Identification, Supervision, and Cost-Reduction Strategies

In this part, we discuss several identification, supervision, and cost-Reduction strategies. Table V summarizes the main features of the works we study in this section.

1) Identification of Participants: MCS is usually influenced by malicious participants. Malicious participants may provide erroneous data to gain benefits and affect the quality of MCS. They even may attack the MCS platform, such as causing the denial of service [126]. One major technique that relieves malicious influence is identification technology, based on whether workers can pass identification when taking part in MCS. This method is good for facing the availability and reliability problems of MCS. Yang *et al.* [19] proposed a distributed authentication mechanism which reduces the number of malicious users by authenticating new users through existing crowdsourcing participants.

2) Quality Supervision: The attraction, speed, and quality are the main factors to assess an MCS system [115]. The quality of MCS can be considered from two perspectives: 1) the quality of data provided by participants and 2) the quality of services provided by the platform. We discuss the quality assurance of data in Section III-B1. The quality of services provided by the platform is generally identified based on the satisfaction of its customers. Pu *et al.* [87] introduced the

TABLE V
SUMMARY OF IDENTIFICATION, SUPERVISION, AND EXPENDITURE REDUCTION TECHNOLOGIES

References	Major contributions	Specialties
Hosio *et al.* [115]	Investigating the workers' behavior and providing economic incentives	Reveals that pricing is an effective mechanism for adjusting the supply of labors
Zhuo *et al.* [116]	A three-party architecture in MCS to implement cloud computing	Simulation results show the feasibility and efficiency of the solution
Xu *et al.* [117]	Compressive crowdsensing that enables compressive sensing techniques	The technology outperforms standard uses of compressive sensing
Cheung *et al.* [118]	A distributed task selection algorithm to help users in task selection	Achieves the highest fairness index
Wang *et al.* [119]	A crowdsensing paradigm for sparse mobile crowdsensing	Sparse MCS applications intelligently select a small portion of a target area for sensing
Wang *et al.* [120]	A platform in which individuals can earn money by completing simple tasks	The system support different types of tasks, *e.g.*, translation, transcription, and surveys

concept of service quality to represent the expected service benefit of crowdsourcing customers. At the same time, feedback mechanisms can be applied to effectively improve the quality of MCS. MCS platforms can change strategies after receiving users' review.

3) Resource Control: Generally, the resources of mobile devices (e.g., memory and battery) are limited. Thus, the resource surplus of workers' devices should be considered in an MCS system. It is indispensable to implement effective resource control mechanisms to reduce data loss while improving MCS quality. Optimizing the data collection process can reduce the energy consumption. The purpose of such optimization is to balance the resource consumption and data quality tradeoff. It is shown that the accuracy of data collected by mobile devices significantly depends on their energy consumption level [33]. Thus, application developers should use appropriate algorithms to reduce the energy consumption while satisfying the data quality. The common approach is to control the process of sensing, uploading, and communication, which reducing the energy consumption of workers. In addition, applying new technologies, such as cloud computing, can reduce the storage, and computing burden of devices [116]. In [117], a compressive sensing technology has been applied to reduce the burden of workers devices and the amount of data collected by workers manually while ensuring the accuracy of data.

4) Cost Reduction: The crowdsourcing platform aims to reduce the cost of hiring workers and system maintenance, whereas workers need to reduce the amount of resources they consume and the traffic costs [118]. In the process of task assignment, the number of workers who participate in particular tasks should be moderated [119]. Some task assigning methods identify the optimal number of workers participate in each task. For example, methods based on environmental perception distribute crowdsourcing tasks to appropriate participants rather than sending them to all available users [72], [84], [120]. In addition, some works choose the closest workers to a particular task as participants to reduce the traffic costs of workers [139]. In addition, some works apply auction mechanisms to balance the budget, which can also reduce the cost [76].

Summary: After tagging and evaluating the tasks, the MCS platform assign them to appropriate workers. MCS processes a large amount of data (e.g., through cloud services). There are three phases in data processing: 1) preprocessing; 2) evaluation; and 3) extraction. Some technologies are used to improve the quality of MCS, such as evaluating participants and incentive mechanism. Effective incentive mechanisms are designed to stimulate the cooperation of mobile participants. The incentives can be provided in forms of money, entertainment, mutual benefit principle etc.

IV. APPLICATIONS OF MCS IN SMART CITIES

MCS plays an important role in the management of smart cities and the improvement of citizens' living standards. Technically, the MCS applications aim at bridging the MCS platform, customers, and workers. In this section, we introduce existing works on the MCS applications in smart cities and highlight their main features in Table VI.

A. Smart Navigation

Location services are the basic services of MCS in smart cities [140], [141]. In the following, we explain popular applications for navigation enabled by MCS in smart cities.

1) Localization: The location-based services use users' location and movement information to provide customized services. For instance, the mobility information of users collected by MCS can provide navigation-based services or enable creating elaborative maps to bicycle riders. Zhang *et al.* [142] applied MCS to build a navigation dataset. Sun *et al.* [110] proposed a secure and privacy-preserving finding system to detect different types of objects, such as children or old people.

2) Building Discovery: Location-based services enabled by MCS can help find particular places, such as hotels and restaurants. Furthermore, MCS can display in-building scenes. The indoor model of a building can be established based on the movement trajectory of participants, which can provide indoor navigation services [129], [143]. Combined with the images and videos taken by mobile users, Gao *et al.* [60]

TABLE VI
APPLICATIONS OF MCS IN DIFFERENT CATEGORIES

Categories	Applications	Cases
Smart Navigation	Localization	Navigation [127], maps [128], finding objects [110]
	Building Discovery	Finding hotels, in-building scenes [129]
Civic Life	Healthcare	Testing body temperature [130], preventing infectious diseases [131]
	Commodity Price	Comparing price of goods [27]
Public Services	Environment Monitoring	Detecting noise pollution [50, 132], air pollution [133, 134]
	Public Safety	Inferring criminal activities [5], reporting natural disasters [135]
	Media and News	Real-time news report [122], collecting rumors [136]
	Communal Facilities	Maintenance of public facilities, reporting damage [111]
	Public Administration	Reporting traffic conditions [22], assessing municipal services [30]
Smart Transportation	Public Transportation	Providing bus routes and arrival information [86]
	Individual Planning	Providing personalized route [86], smart parking [85]
	Traffic Flow	Detecting traffic anomaly [137], guiding taxis [138]

used the crowdsourcing data to generate the complete floor plan, including corridor connection, room size, and shape.

B. Civic Life

Applications based on MCS greatly facilitate the lives of citizens. We describe some general applications in the lives of citizens.

1) Healthcare: MCS has great promise in mobile health applications [144]. The majority of mobile devices are expected to be equipped with health sensors which will enable them to test a user's health status, e.g., body temperature, heartbeat, breathing, diet, sleep, and exercise. Kanhere [27] developed a health management system for mobile users that collect data from mobile users and perceive their health status real time. Pryss *et al.* [145] proposed an MCS application for tinnitus assessment, therapy and research. The application can give suggestions based on users' living habits, such as do more exercise and regular diet. Brabham *et al.* [146] took advantage of MCS to contribute to public health, wherein a large number of mobile users' health conditions are collected to detect large-scale infectious diseases as early as possible.

2) Commodity Price: Sharing the price of commodities by mobile users is another application of MCS in smart cities. Using MCS, citizens can be timely informed about commodity prices. Some applications encourage people to upload the price tag of goods they shop [27].

C. Public Services

The data and information collected by MCS techniques can enhance the service level of smart cities and help governments to improve city management facilities. We introduce servel representative applications about public services as follows.

1) Environment Monitoring: Today, noise pollution, air pollution, and water pollution significantly affect human life. People are environmentally conscious, and they are concerned about the health status of cities and public places. Hence, how to monitor the quality of environments is of paramount importance. Recently, some existing works have employed MCS technologies to monitor the environment quality in terms of different factors. A noise map system using MCS has low resource consumption and high accuracy [132]. By attaching sensors to GPS-enabled cell phones, Honicky *et al.* [134] explored MCS data and achieve real-time atmospheric detection. Ganti *et al.* [33] monitored the environmental quality of a city in real time by MCS. Pan *et al.* [51] designed an application, called AirTick, to produce accurate estimates of air quality, where users can use the application to check the situation of a particular location to make an appropriate travel plan. Some applications have been also developed to help users monitor pollution and urban noise pollution [27], [50].

2) Public Safety: Public safety involves different emergency scenarios, such as criminal activities, disasters, and diseases. Although many cameras and monitors have been developed in smart city, it may not still be easy to realize abnormal activities. In addition, it is difficult for monitoring systems to identify some crimes, such as abduction of children. The application of MCS can mobilize the power of masses to promote public safety. By analyzing human movements, the security services can detect anomalies and infer criminal activities, such as terrorist attacks [5]. Meanwhile, individuals can report traffic safety problems or traffic violations [22]. In addition, system of system (SOS) systems can be associated with wearable devices to provide security for individuals [37]. For example, Huang *et al.* [147] designed an MCS application for campus safety in which a user can call the police when it is in danger. MCS can also contribute to disaster responses. People can report disaster situations online to help with the disaster prevention and rescue activities. In addition, the government can track, report, or coordinate relief efforts based on information generated by MCS [135].

3) Social Media and News Report: MCS enriches social media content and provides opportunities for news reporting methods. Participants can easily submit photographs, videos, and comments via their mobile devices, which helps the media learn about real-time events. At the same time, location-based news can be reports [122]. In addition, MCS play a role in emotional problems, such as judging the emotion of blogs or news [148]. MCS can also be applied to image translation, annotation, and classification. Foreign tourists, for example, can ask questions about an image and locals can assist them [149]. Moreover, MCS can help collect information about rumors about rumorers [136]. To filter spam messages in social networks, Yadav *et al.* [150] used crowdfunding to design a filtering mechanism for text messages.

4) Communal Facilities: The management and maintenance of public facilities in a city often lack of pertinence and waste a lot of financial resources. MCS can help councils understand the state of public facilities. For example, citizens can report damages they observe to public facilities and street lamps [111]. The coverage and signal strength of a public network in a region can also be discovered using MCS [114].

5) Public Administration: MCS provides citizens with the opportunity to directly participate in public administration to reduce the barriers between citizens and public administrations [80]. Citizens can report traffic conditions and help improve urban traffic. Motta *et al.* [30] established a four-stage model to assess the maturity of municipal services that can help governments and local sectors to improve their services.

D. Smart Transportation

The increasing number of road accidents, traffic congestion, parking chaos, and other similar problems have become the major obstacles for the realization of smart cities [151]. To deal with this, in 2015, the U.S. Department of Transportation launched "smart city challenge." The competition encourages cities integrate data from multiple sources to create accurate models in transportation, environment, and energy. Many novel traffic applications were proposed, such as shared trunk traffic data, on-demand delivery trucks, and programmable city streets. Those applications aim at employing MCS applications to enable residents to take part in the process of making cities smarter. In the following, we highlight the applications of MCS in traffic management and planing.

1) Public Transportation: Although public transportations (e.g., buses and trains) has strong regularity, complex routes can bring inconvenience to citizens. Nandan *et al.* [26] designed an application for bus route searching, which covers bus routes and arrival information. Location-based services can provide information about each site [86]. Similarly, Steinfeld *et al.* [152] used MCS to collect location information about buses and the number of passengers to predict the arrival time of buses.

2) Individual Planning: Finding an optimal route for individuals in a complex network of smart cities is nontrivial. For example, over 100 million drivers use Waze[2] to share real-time traffic road information and save fee of fuel. Bajaj *et al.* [86] focused on providing users with the most convenient personalized routes. In [128], individuals with disabilities and disabled are also taken into account. Another frequently used planning application is smart parking. Yan *et al.* [121] designed a mobile crowdsourcing platform for parking reservation which can obtain booking information of parking lots and use them to help other users in car parking. In [85], parking guidance is integrated into the road navigation system in which drivers are both consumers and workers. The use of MCS can improve the efficiency of parking and alleviates congestion in urban traffic [153].

[2]https://www.waze.com/

3) Traffic Flow: Inlining with big data technologies, MCS can analyze urban traffic flows to deal with traffic congestions [154]–[156]. For example, Kong *et al.* [137] analyzed the long-term traffic anomaly in traffic, which is helpful in the transportation management of smart cities. Another function of traffic flow is improving traffic efficiency. For example, a traffic flow monitoring application can guide taxis to place their passengers in less crowded places [28], [138], [151].

Summary: MCS applications bridges the platform, users, and workers to improve the city management level and citizens' living standards. MCS has been widely used in different fields, such as public services, environmental monitoring, health monitoring, public safety, and transportation to make the city smarter.

V. Visions and Future Challenges

In the previous sections, we have surveyed some key issues and applications of MCS in smart cities. While a wide range of MCS technologies and applications in smart cities are discussed, a large number of potential problems and challenges both at the theoretical and applied levels should be further explored. In addition, the social or psychological challenges also hinder MCS [26]. In the rest of this section, we introduce several important and unexplored challenges for MCS in smart cities as the future research directions.

A. Scarce Resources

The power and storage resources in mobile devices are often scarce that affects the operation and performance of MCS in different ways. For battery-operated devices, designers must consider the influence of topology selection and decision implementation in MCS. One of the evading methods is parallelizing the application functions by efficient tasks allocation mechanisms [38]. Another limitation is energy consumption of mobile devices because of their energy-expensive characteristics. Universally, smartphones have communication mediums which consume an enormous amount of energy in terms of unsymmetrical upload/download links [16]. To deal with this challenge, administrators should use information, such as user preferences, skills, and reliability to intelligently distribute MCS tasks. Moreover, tasks should be scheduled efficiently to minimize the network load [52].

B. Privacy Control

The MCS platforms are usually inclined to use the context information of workers (such as, the location and environment information) to provide appropriate MCS task recommendations. However, optimal allocation of tasks can improve the quality of service, but it may cause privacy disclosure if the platform is attacked [84]. Presently, researchers aim at developing solutions for privacy preservation. The anonymity [126], the subscription trapdoor [19], and punishment mechanisms [89] are relatively effective solutions in this context. The possible research ideas are further surveying the specific privacy and security concerns of users, which can be linked with their different characteristics [48]. In this context, Lin *et al.* [157] proposed a privacy assessment technique that uses MCS to obtain the users' expectations from mobile applications using sensitive resources.

C. Trustworthy Assessment of Information

To provide mobility services to users through MCS, the trustworthiness of MCS data should be highly evaluated. To this aim, a trustable MCS Platform should be capable of assessing the reliability of devices and filtering the negative and untrusted devices [27]. There are still many dishonest mobile detectors, which prevent assessing the trustworthiness of information [110]. How to build a strong assessing mechanism is very challenging and unexplored. The assessing mechanisms designed by administrators should balance between the user security and operating efficiency.

D. Heterogeneity of Hardware and Platforms

MCS systems may employ different types of communication and networking technologies, such as cellular, Wi-Fi, and Bluetooth. In addition, mobile devices used in MCS are generally multifarious as well [19]. The capture results in different values across heterogeneous hardware, which leads to measurement variance [158]. These phenomena cause the generation of heterogeneous data. Besides, mobile devices are highly dynamics in terms of functionality, which make it more difficult to provide a general power and bandwidth resources to model and predict specific tasks [33]. Apart from the sensing hardware devices, different mobile platforms (such as Android, iOS, and Windows) and even different versions of each platform have highly heterogeneity. The heterogeneities of hardware and platforms are positively correlated with the complexity of the crowdsensing application space.

E. Nonparticipatory Observation

To date, nonparticipatory observation methods have been widely used to capture animal behavior. As the same, it is possible to apply these principles and methodologies to capturing and assessing human behavior [159]. Compared to participatory data capture, nonparticipatory observation is easy to accept and is definitely the future for MCS. Recently, some scholars have addressed nonparticipatory MCS. For example, Kulshrestha *et al.* [160] proposed a smartphone-based nonparticipatory crowd system to monitor the movement patterns of people. The nonparticipatory observation also raises new challenges. On the one hand, the determination of sampling time affects the validity and scale of data. On the other hand, location-tagging the data automatically is extremely challenging.

F. Conflict Avoidance

MCS has a strong diversity and complexity, which can cause major conflicts in actual applications. In MCS systems, there are various device platforms and network topologies. Moreover, different types of MCS data and storage mechanisms are applied. These factors can make conflicts in MCS. Besides, the sensing regions may overlap, which leads to the conflict [59]. Conflict avoidance is still an open issue in MCS, especially in more and more complex environment. This is a critical demand to make a balance between the conflict and efficiency, especially in a resource-constrained environment.

G. Internet of People

Recently, system developers and researchers pay a significant attention to the relation between people and the Internet access models [161]. The advance of mobile devices and wireless networks enhance human interaction, which promotes the appearance of Internet of People (IoP). IoP refers to digital connectivity of people through the Internet infrastructure forming a network of collective intelligence and stimulating interactive communication among people. Unlike the traditional Internet, mobile devices and their carriers become active elements of the Internet. People are not only the end-users but also can produce and deliver services to each other [162]. MCS is one of the preliminary building blocks for IoP framework [163]. How to build an IoP framework by investigating and refining MCS has becomes a promising solution.

Summary: MCS faces potential problems and challenges both at the theoretical and applied perspectives. The limited energy resources of mobile devices is a major concern. The MCS platforms have to deal with privacy protection and security challenges. The MCS platforms should efficiently manage dynamic participants in heterogeneous environments. Constructing MCS systems based on IoT and IoP frameworks is a promising solution.

VI. Conclusion

This paper presented a comprehensive review of mobile crowdsourcing (MCS) in smart cities. In particular, we study enabling technologies for MCS in smart cities, including task management, data collection, incentive mechanisms, as well as supervision and cost reduction technologies. Next, we introduce a wide and diverse range of applications of MCS in smart cities, such as location-based, public, and traffic managements and monitoring applications. Finally, we highlighted the several open challenges and future research directions. We hope that our contributions in this paper will open the new horizons for future research in this challenging area and encouraging application and system designers to develop appealing MCS solutions in smart cities.

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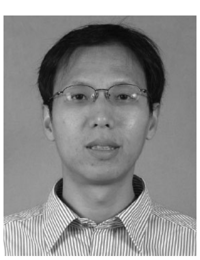

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