When Crowdsensing Meets Smart Cities: A Comprehensive Survey and New Perspectives

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When Crowdsensing Meets Smart Cities: A Comprehensive Survey and New Perspectives

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***Abstract*—Crowdsensing has received widespread attention in recent years. It is extensively employed in smart cities and intelligent transportation systems. This paper comprehensively surveys the latest research advancements in crowdsensing for smart cities from a novel perspective. Specifically, this paper is categorized according to sensing entities in smart cities, including human-oriented sensing, vehicle-oriented sensing, and infrastructure-oriented sensing. Meanwhile, the development of Unmanned Aerial Vehicle (UAV)-assisted sensing in recent years is also summarized, accompanied by a timeline of related research. To facilitate easy comprehension, this paper then positions the reading flow into the corresponding architectures, resolved problems, existing technical solutions, and specific application scenarios for different sensing entities. In particular, the problems to be solved are further analyzed from four technical perspectives, namely mathematics and operational research, artificial intelligence and machine learning, incentive mechanisms, security and privacy protection. Based on the proposed taxonomy, recent studies are thoroughly classified and summarized to illustrate the current state of research in crowdsensing. Furthermore, this paper highlights the emerging applications of human-oriented and vehicle-oriented sensing in smart cities, as well as the frameworks, platforms, simulators, and datasets involved in crowdsensing. Finally, this paper discusses research directions related to crowdsensing in smart cities, such as digital twins, metaverses, and artificial intelligence-generated content. The primary goal of this survey is to review and synthesize prior research, identify potential avenues for future research, and explore opportunities for collaboration with other relevant research domains.**

***Index Terms*—Crowdsensing, smart cities, incentive mechanisms, optimization, artificial intelligence, UAV-assisted sensing.**

I. Introduction

A. Background

Recently, with the rapid development of 5G/6G communication technology and sensor technology, smart cities have entered the era of the intelligent Internet of Everything (IoE). In smart cities, an integrated network architecture of "terminal-edge-cloud" has been gradually established, which brings significant advantages to the development of crowdsensing [1], [2]. In smart cities, humans, terminal devices, vehicles, infrastructures, etc., can all be used as sensing entities to support the realization of crowdsensing. Traditionally, various infrastructures built in smart cities can be used to complete sensing tasks, such as urban monitoring facilities, environmental monitoring equipment, noise monitoring equipment, etc. However, sensing in this way is limited in areas with underdeveloped infrastructures.

Fortunately, Mobile CrowdSensing (MCS) has been applied to constructing smart cities. As reported by the Global System for Mobile Communications Association (GSMA), the number of global Mobile Devices (MDs) has reached 5.3 billion in 2022, with a coverage rate of 67%. These MDs are equipped with powerful sensing modules, such as GPS, accelerometers, microphones, and cameras, to sense relevant information in smart cities ubiquitously. In MCS, each Mobile User (MU) carrying a sensing device is considered as an independent entity. Large-scale and complex social sensing tasks can be accomplished through cooperation among MUs. The most crucial feature of MCS is that MUs will be involved in each process of the entire system lifecycle, including data sensing, transmission, analysis, and application [3]. Compared to traditional sensor networks, MCS boasts several advantages, such as low data collection costs, ease of device maintenance, and scalable system architecture. This has also facilitated the emergence of numerous applications in smart cities, including environmental monitoring, traffic monitoring, and social management [4]. Meanwhile, these applications can better serve the construction of smart cities.

In addition, ubiquitous vehicles have played an important role in smart cities. As vehicles have become networked and intelligent, they have transformed from a convenient means of transportation into a powerful platform for mobile sensing, computing, and storage [5]. This has led to the emergence of Vehicular CrowdSensing (VCS). Specifically, vehicles serve as the basic sensing units in VCS. It supports Internet of Vehicles (IoV) services, enabling coordination between humans, vehicles, and the environment in urban road traffic scenarios. Meanwhile, vehicles are mobile and flexibly operated, which can support large-scale natural and social sensing needs in smart cities [6]. Specifically, typical natural sensing tasks include monitoring road conditions, air quality, temperature,

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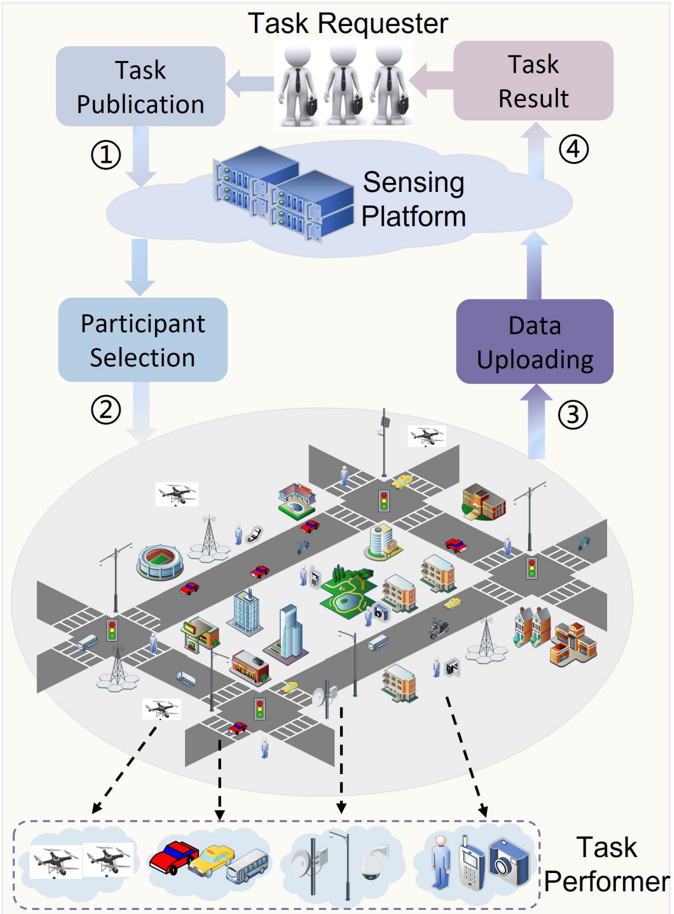

Fig. 1. The example of task performs process in smart cities scenarios. ① The task requester publishes the sensing task. ② The platform selects appropriate participants to perform the task. ③ Task performers complete tasks and upload sensing data. ④ The platform processes the data and returns the results to the task requester.

TABLE I

Nomenclature	
MD	Mobile Device
MCS	Mobile Crowd Sensing
MU	Mobile User
VCS	Vehicular Crowd Sensing
IoE	Internet of Everything
IoV	Internet of Vehicle
AI	Artificial Intelligence
ML	Machine Learning
QoS	Quality of Service
IoT	Internet of Thing
V2V	Vehicle to Vehicle
V2R	Vehicle to Road side unit
WSN	Wireless Sensor Network
DL	Deep Learning
CNN	Convolution Neural Networks
RNN	Recurrent Neural Network
GCN	Graph Convolutional Network
GAT	Graph Attention Network
RL	Reinforcement Learning
DRL	Deep Reinforcement Learning
DQN	Deep Q-learning
AC	Actor-Critic
DDQN	Double DQN
A3C	Asynchronous Advantage Actor-Critic
DDPG	Deep Deterministic Policy Gradient
NE	Nash Equilibrium
UAV	Unmanned Aerial Vehicle
PDR	Pedestrian Dead Reckoning
PPO	Proximal Policy Optimization
DCN	Deep Convolutional Network
GAN	Generative Adversarial Network
DT	Digital Twin
AIGC	AI-Generated Content

noise, etc., while social sensing tasks encompass monitoring traffic conditions, social events, and crowd activities.

Traffic condition monitoring in smart cities is showcased as an example. Generally, authorities would often rely on various sensing infrastructures, such as cameras, stationed across the city to monitor traffic conditions. However, this approach has suffered from coverage and incurs high maintenance costs. With the advent of VCS, traffic monitoring tasks can be assigned to vehicles that are willing to participate. Using onboard cameras, these vehicles can take pictures or video at designated locations to support traffic condition analysis. The captured content and GPS information are uploaded to the platform for analysis, and the results are conveyed to the task requester (the traffic department). The sensing task performs process is depicted in Fig. 1. From the perspective of requesters, VCS is a more cost-effective solution compared to traditional methods and represents a promising direction for smart cities application [7].

The above example shows that the crowdsensing system consists of three primary components: the task requester, the platform, and the task performer. Entities with sensing requirements can act as task requesters by posting related tasks on the platform. At the same time, they can also specify related constraints, such as time, location, cost, etc. The platform then assigns the task to selected performers, such as humans, vehicles, or infrastructures, and provides corresponding rewards. After executing the sensing task, the performer uploads the sensing results to the platform for processing and ultimately returns the results to the requester [8].

B. Motivation

Crowdsensing presents a novel direction for the development of smart cities. However, establishing a stable and sustainable crowdsensing system confronts several problems. Here, vehicles perform sensing tasks more difficult than MUs due to their mobility, but they also have potential advantages. The expansion of the sensing range and refinement of the sensing granularity by vehicles is an important aspect to consider. Additionally, participants in crowdsensing systems are typically motivated by self-interest and require compensation to perform tasks. It is necessary to find ways to motivate participants to engage in sensing tasks. Similarly, there are questions regarding the platform's ability to allocate sensing tasks in a manner that aligns with its own interests, to protect the privacy and data security of participants, and to guarantee the quality of sensing data within various constraints. Lastly, humans and vehicles need to be sensed collaboratively with urban infrastructure to improve sensing efficiency. Addressing

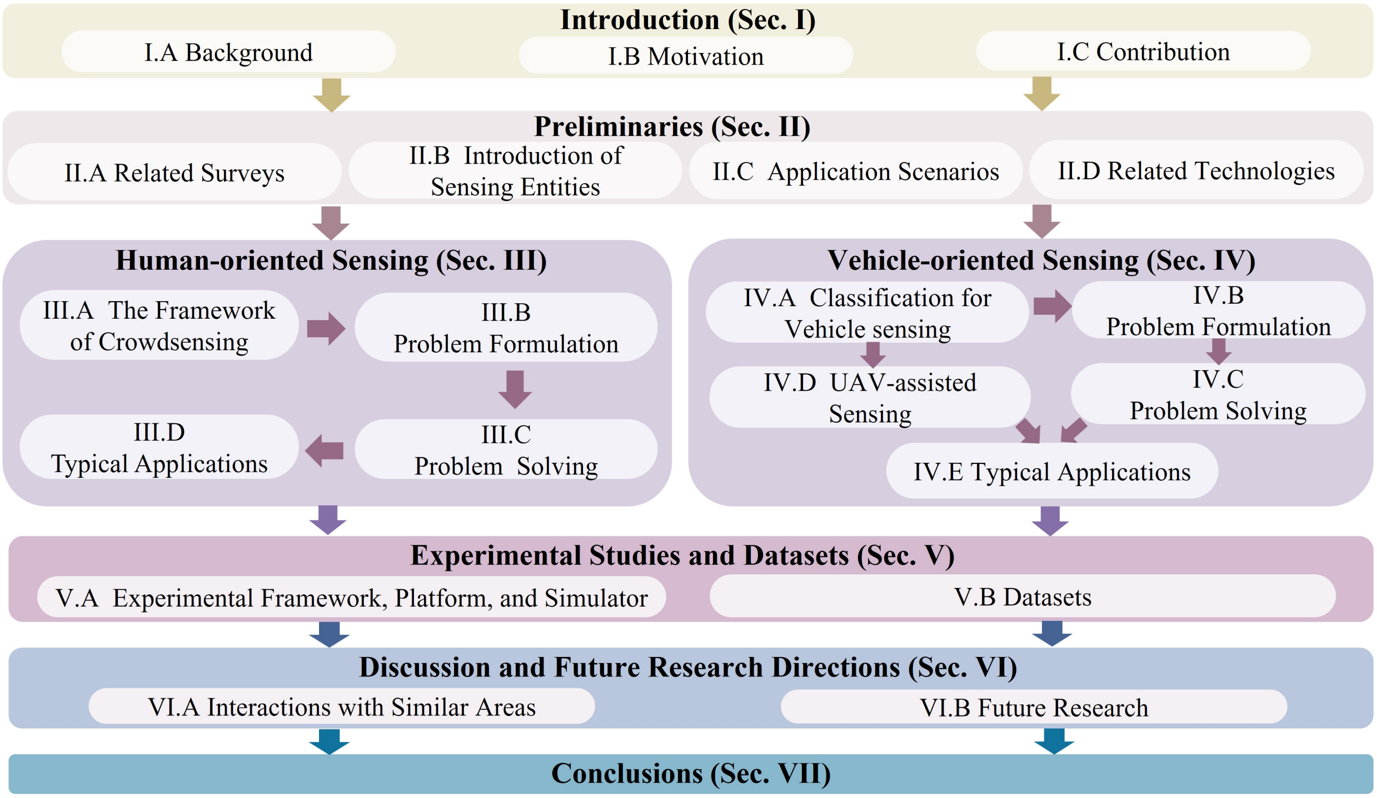

Fig. 2. The survey organization.

these challenges is crucial for advancing the development of smart cities through crowdsensing.

In the past few years, certain researchers have focused on single aspects of crowdsensing, such as incentive mechanism [9], [10], privacy protection [11], [12], and resource optimization [13], [14]. In addition, other researchers have summarised MCS from a comprehensive perspective [15], [16]. Liu *et al.* [15] classified MCS from a data perspective, and Capponi *et al.* [16] divided the MCS process into a four-tier architecture. This will be explained in detail in section II-A. Different from the above studies, on the one hand, we investigated crowdsensing from different perspectives, which is driven by the application of crowdsensing in smart cities. On the other hand, significant progress has been made in crowdsensing over the past five years, especially in studying the application of crowdsensing in smart cities. Moreover, Artificial Intelligence (AI) and the IoV have facilitated the prosperity of crowdsensing.

C. Contribution

Distinct from existing surveys and tutorials, this survey starts from the perspective of sensing entities in smart cities, and focuses on the problems faced in different sensing entity scenarios. It is important to note that infrastructure-oriented sensing is often combined with human-oriented and vehicle-oriented sensing.

Firstly, we summarize the relevant reviews and highlight the novelty of our survey. Here, relevant sensing entities and application scenarios are also presented. Secondly, this survey presents the problems that need to be solved in different sensing entity scenarios. Then, four main technology classifications are proposed to solve these problems. Specifically, it is mainly divided into mathematics and operational research, AI and machine learning (ML), incentive mechanisms, security and privacy protection. Thirdly, this survey presents a comprehensive classification and summary of the frameworks, problem-solving technologies, and crowdsensing applications for sensing entities in smart cities. Importantly, this survey focuses on the application of Unmanned Aerial Vehicles (UAV) sensing in smart city scenarios. A timeline of research developments related to UAV-assisted sensing is also described. Fourthly, this survey highlights existing simulators, platforms, and applied datasets for crowdsensing. Finally, future research directions and potential solutions for crowdsensing in smart cities are outlined. The combination of crowdsensing with crowd computing, Digital Twins (DT), Metaverse, and AI-Generated Content (AIGC) services can promote the better development of smart cities. The relevant terms involved in this survey are summarized in Table I.

The contributions of this survey are summarized as follows:

1) According to different sensing entities in smart cities, the survey divides crowdsensing into human-oriented sensing, vehicle-oriented sensing, and infrastructure-oriented sensing. Then, applications in smart cities for different sensing entities are summarized respectively. The latest developments in crowdsensing in smart cities are also

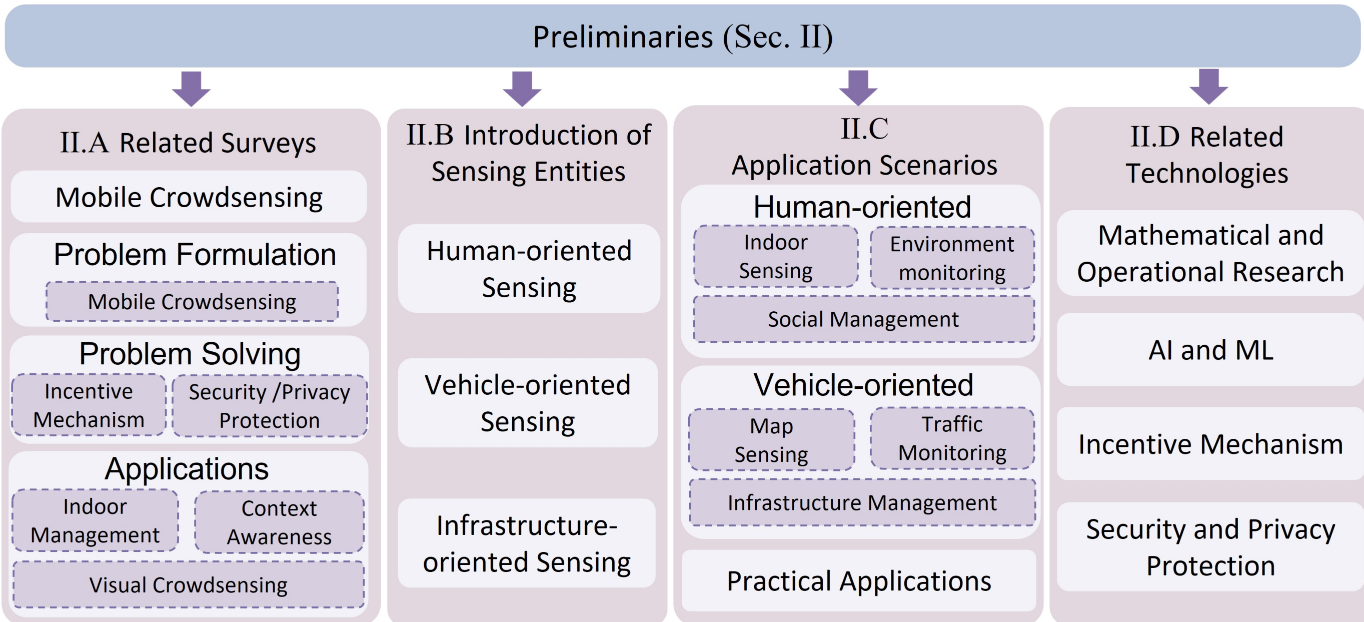

Fig. 3. The structure of section II.

outlined.

2) The survey identifies the problems faced in different sensing entity scenarios. Then, the existing studies are classified and summarized from four technical perspectives. The focus is on human-oriented sensing and vehicle-oriented sensing. Importantly, the development of UAV-assisted sensing is also reviewed.
3) The survey summarizes existing frameworks, simulators, and platforms of crowdsensing. Meanwhile, according to different sensing entities, related datasets of crowdsensing applied to smart city scenarios are classified.
4) The survey also discusses areas close to crowdsensing and illustrates their connections. Moreover, future research directions and potential solutions in smart cities are identified to guide the development of crowdsensing.

The rest of this survey is organized as follows. Section II introduces related surveys, the sensing entities in smart cities, and related technologies. Section III provides a systematic classification and summary for human-oriented sensing, respectively, and introduces related applications. Section IV introduces the classification, problems, solutions and application scenarios for vehicle-oriented sensing. Section V introduces related frameworks, platforms, simulators, and datasets. Section VI discusses the interactions with similar areas, and analyzes future research directions and potential solutions. Finally, this survey is summarized in Section VII. Fig. 2 shows the organizational framework of this survey.

II. Preliminaries

In this section, we first review recent surveys on crowdsensing and highlight the differences with this survey. Then, we introduce the sensing entities in smart cities and associated application scenarios. Finally, we discuss related technologies applied to crowdsensing in smart cities. Fig. 3 shows the organization of section II.

A. Related Surveys

In this subsection, we present an overview of the recent surveys on crowdsensing. It is then categorized in terms of problem formulation, problem solving and application. Table II summarizes and differentiates the existing surveys.

1) Mobile Crowdsensing: In the past few years, researchers have conducted comprehensive reviews of MCS. They mainly focus on human-oriented sensing, or analysis from the data perspective. Liu *et al.* in [15] investigated the incentive mechanism, security, and privacy protection in MCS from the data perspective. Specifically, data collection, data analysis, and data application in MCS are studied. In [16], Capponi *et al.* classified MCS into four layers: sensing, communication, data, and application layers. As one of the early studies, Guo *et al.* in [17] described the emerging human sensing and proposed a human-based sensing system framework. In addition, the complementarity of human-machine fusion sensing is also described, which lays the foundation for later research. Ganti *et al.* in [18] divided MCS into participatory and opportunistic sensing, investigating relevant characteristics and applications. Liu *et al.* in [19] analyzed and summarized crowdsensing from the perspective of Quality of Service (QoS).

2) Task Allocation: Optimal task allocation is one of the most critical targets in crowdsensing. The quality of sensing task completion can be improved through reasonable allocation, and the execution cost can be reduced. In [13], Wang *et al.* discussed and summarized the allocation of sensing tasks in detail. Then, according to different types of problems, the corresponding design ideas and solutions are given. Chen *et al.* in [14] focused on the matching between tasks and participants. In addition, a targeted matching framework and corresponding scheme design are proposed.

3) Incentive Mechanism: As it is difficult for participants to actively participate in the sensing process without a reward, researchers have conducted extensive research on motivating

TABLE II
COMPARISON OF EXISTING RELEVANT REVIEWS

Type	Topic		References	Description
Comprehensive	Mobile Crowdsensing		Guo *et al.* [17], 2015	Survey on human-based sensing system
			Liu *et al.* [15], 2019	Investigate the incentive mechanism, security, and privacy protection in MCS from the data perspective
			Capponi *et al.* [16], 2019	Classify MCS into four layers: sensing, communication, data, and application layer
			Ganti *et al.* [18], 2011	Discuss participatory and opportunistic sensing
			Liu *et al.* [19], 2018	Summarize crowdsensing from the perspective of Quality of Service (QoS)
Concentrated	Problem Formulation	Task Allocation	Wang *et al.* [13], 2018	Summarize the allocation of sensing tasks from different types
			Chen *et al.* [14], 2018	Focus on the matching between tasks and participants
	Problem Solving	Incentive Mechanism	Dasari *et al.* [20], 2020	Survey on game theory-based soluctions in MCS
			Jaimes *et al.* [10]	Classify the incentive mechanisms in MCS and considered both online and offline scenarios
			Gao *et al.* [9], 2015	Discuss the incentive mechanism in participatory sensing
		Security and Privacy Protection	Vergara *et al.* [11], 2017	Describe the design of privacy-preserving related techniques in crowdsensing
			Cheng *et al.* [12], 2022	Survey on privacy-preserving technologies in MCS
	Application	Indoor Management	Lashkari *et al.* [21], 2019	Classify the indoor positioning solutions in MCS
			Pei *et al.* [22], 2016	Discuss the mobile indoor positioning in MCS
		Context Awareness	Hamed *et al.* [23], 2019	Analyze crowdsensing based on context information
			Chan *et al.* [24], 2020	Consider the combination of smartphones and context awareness for abnormal driver behavior detection
		Visual Crowdsensing	Yang *et al.* [25], 2021	Investigate the research and applications of visual crowdsensing in different fields
			Guo *et al.* [26], 2017	Discusse the framework, key technologies, application fields, and future challenges of visual sensing
A comprehensive survey of crowdsensing towards smart cities			**Ours Survey, 2023**	Investigate the development and application of crowdsensing in smart cities. Discuss the problems and solutions faced in different entity scenarios. Identify existing challenges and future research directions.

participants. In [9], Gao *et al.* investigated the incentive mechanism in participatory sensing. Then, motivation strategies, frameworks, and system implementations in participatory sensing are summarized. Jaimes *et al.* in [10] reviewed and classified the incentive mechanisms in crowdsensing, considering both online and offline scenarios. In addition, constraint mechanisms are also designed to evaluate the performance of various incentive methods. Dasari *et al.* in [20] summarized different game theory solutions, which usually occur between the platform and participants. The platform aims to minimize costs, while the participants aim to maximize their interests. In addition, game models under complete and incomplete information scenarios are analyzed.

4) Security and Privacy Protection: During the sensing process, a large amount of private data will be generated, which is easy to cause security problems. Therefore, protecting the privacy and security of sensing data becomes crucial. In [11], authors described the design of privacy-preserving related techniques in crowdsensing. Then, related technologies are classified and evaluated. This avoids the situation where some participants refuse to participate in a sensing task because privacy cannot be guaranteed. Similarly, Cheng *et al.* in [12] surveyed the current state of development of crowdsensing in digital cities. Then, related privacy-preserving techniques are classified and evaluated.

5) Indoor Management: Real-time positioning and navigation can be realized in indoor scenes through the sensing ability of smartphones. In [21], authors classified the indoor positioning solutions based on crowdsensing. It is then explained which crowd-based approaches were used in each solution. In [22], Pei *et al.* discussed mobile indoor positioning based on crowdsensing. It also determines that crowdsensing is a low-cost solution for building fingerprint databases.

6) Context Awareness: Understanding the context information of MUs is critical for the accuracy of presented data. In [23], authors proposed a corresponding framework for context awareness. Then the crowdsensing based on context information is analyzed from conceptual, context awareness and function perspectives. Authors in [24] comprehensively reviewed the methods of abnormal driver behaviour detection. Then, smartphone and context awareness are combined to improve detection effectiveness.

7) Visual Crowdsensing: Cameras can play an important role in the sensing process, including surveillance facilities in cities and cameras in terminal devices. Yang *et al.* in [25] investigated the research and applications of visual sensing in different fields. Then the visual sensing technology is classified in detail. In [26], Guo *et al.* introduced the concept, function, and application field of visual sensing. Then, key visual sensing technologies are investigated, and future challenges are analyzed.

The Novelty of This Survey: We have comprehensively summarized the latest research on crowdsensing in the last five years, which goes beyond the above work. This is driven by the rapid development of crowdsensing in smart cities. The focus is to classify current work from the perspective of sensing entities in smart city scenarios, specifically including human-oriented sensing, vehicle-oriented sensing, and infrastructure-oriented sensing. This can highlight the different issues and challenges in different sensing entities scenarios. In particular, we provide a detailed summary of UAV-assisted sensing and give a timeline of the development of related research.

We provide an overview of problems faced in human-oriented and vehicle-oriented sensing. Then, the studies on solving these problems are classified from four technical perspectives. The four technical perspectives are mathematics and operational research, AL and ML, incentive mechanism, security and privacy protection. We introduce the applications in smart cities for different sensing entities scenarios separately. We also summarize the framework, platform, and simulators related to crowdsensing. Here, according to different sensing entities in smart cities, datasets applied in recent studies are classified. Finally, we discuss future research directions for crowdsensing in smart cities, including crowd computing, digital twins, and metaverses.

B. Introduction of Sensing Entities

In this subsection, we introduce sensing entities in smart cities. In smart cities, sensing entities are mainly divided into three categories, namely, human-oriented, vehicle-oriented, and infrastructure-oriented. Typically, infrastructure-oriented sensing entities can collaborate with the other two types. Fig. 4 shows sensing entities in smart city scenarios.

1) Human-oriented Sensing: Initially, the participants in crowdsensing were human workers, introduced through the concept of crowdsourcing. The sensing tasks are issued by the platform and executed by workers. Some of these workers move randomly, some have fixed starting and ending locations, and some have fixed routes.

With the development of IoTs and intelligent devices in recent years, mobile terminal devices held by MUs have gradually become sensing entities. These terminal devices include smartphones, cameras, video cameras, etc. In fact, the mobile terminal device also needs to be operated by MU to complete the sensing task. As mobile terminal devices are owned by the MU, it is still classified as human-oriented sensing.

2) Vehicle-oriented Sensing: As vehicles become networked and intelligent, they gradually transform into mobile platforms for sensing, computing, and storage. Therefore, vehicles have gradually become sensing entities widely used in smart city scenarios.

Certain vehicles usually have their original tasks, such as taxis and buses, which must follow a fixed trajectory. They need to follow the planned trajectories in the city and can

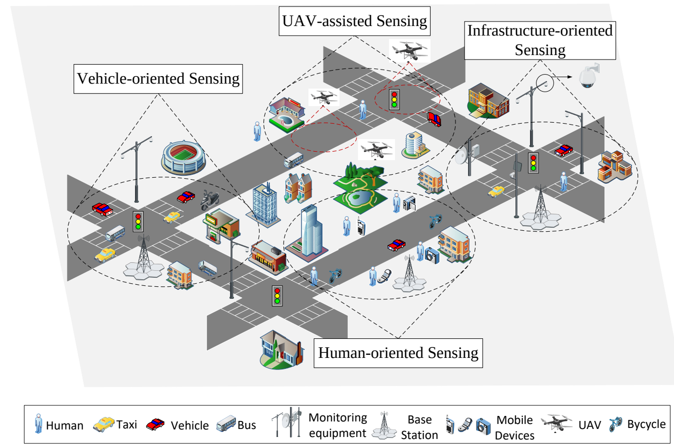

Fig. 4. The sensing entities in smart city scenarios.

complete sensing tasks on their trajectories. Such vehicles are known as opportunistic sensing vehicles. With the development of autonomous driving, autonomous vehicles can act as specialist sensing devices and actively adapt their trajectory to the location of sensing tasks. Similarly, private vehicles can change their original trajectory to perform sensing tasks according to the task location. Such vehicles are also known as participatory sensing vehicles.

Unlike ground vehicles, UAVs have more flexible mobility and are unaffected by road traffic fluctuation. It can access diverse locations that are inaccessible to vehicles, such as emergency situations. Moreover, UAVs can also serve as air-based sensing entities and collaborate with ground vehicles to accomplish sensing tasks.

3) Infrastructure-oriented Sensing: There are several static infrastructures in cities which can act as sensing entities. Here, monitoring equipment is spread all over the city. It can not only complete the original monitoring task but also complete the sensing task. Specifically, real-time traffic flow can be recorded by taking photos or videos. Based on these data, the current traffic situation can be analyzed. In addition, traffic accidents and other emergencies can be judged in time through the real-time monitoring system.

Then, several professional sensing devices are installed in the city, for example, air pollution monitoring equipment, noise monitoring equipment, etc. These professional sensing devices can provide accurate sensing data. However, in areas lacking infrastructure, human-carried equipment or vehicles are needed to assist in the sensing task [27].

C. Application Scenarios

In recent years, crowdsensing has been increasingly employed across various applications, particularly in smart cities and intelligent transportation. This subsection briefly introduces the application scenarios and research in Section III-D and Section IV-E. Likewise, we classify them according to human-oriented and vehicle-oriented sensing scenarios. Note that infrastructure-oriented sensing applications often combine the two categories above. At last, we introduce the sensing system construction of Huawei in smart cities to further illustrate the practical application.

1) Human-oriented Sensing Scenarios: Human-oriented sensing scenarios are divided into indoor sensing, environmental monitoring, social management, etc.

- **Indoor sensing**: With the sensor of MDs, it can be applied in many indoor scenarios. As conventional GPS positioning is inefficient in indoor scenarios, indoor maps can be constructed with the sensing capabilities of MDs. Specifically, the radio frequency fingerprint of cellular signal or WiFi can be used for indoor high-precision positioning [28].
- **Environment monitoring**: MUs can usually sense in real-time at their location to respond to real-time events in a timely manner. This can often be combined with infrastructure-oriented sensing. In smart cities, frequently used scenarios include noise monitoring, light pollution monitoring at night, air quality monitoring, etc [29].
- **Social Management**: MUs can participate in social sensing tasks like city accident monitoring. It takes photos through mobile phones and submits them to the platform for timely handling of emergencies. Regarding public health, health monitoring can be accomplished by gathering data from the user's wearable device. In the area of public safety, information can be released online by the relevant authorities. People can upload the found evidence to the platform, and relevant departments can handle cases online. In the field of smart agriculture, professional data collection can be carried out through MDs to judge the growth of crops. Additionally, human movement patterns and preferences can be used to study social relationships for viral transmission analysis [30].

2) Vehicle-oriented Sensing Scenarios: Due to the mobility of vehicles, there are wider possibilities for vehicle-oriented sensing scenarios. Currently, the sensing scenarios for vehicle dispatching mainly include map sensing, traffic monitoring, infrastructure management, etc.

- **Map Sensing**: Traditional map creation requires specialist map collection equipment, which is costly and slow to update. As intelligent vehicles improve their sensing capabilities, it is becoming more convenient to create and update sensing maps through vehicles. It does not need professional threshold restrictions, nor does it need expensive costs. It can be completed with the help of onboard cameras or radar. Recent studies have focused on crowdsensing map construction, including high-resolution maps, lane-level maps, and intersection maps [31].
- **Traffic Monitoring**: Generally, GPS trajectory can be used for traffic monitoring. The current traffic flow can be determined based on the spatiotemporal characteristics of the GPS trajectory, and corresponding travel suggestions can be provided to the driver. According to GPS information, traffic control identification can also be carried out. Traditional methods require real-time observation of the entire road to provide accurate results, and the cost is immeasurable. By analyzing the GPS track of the vehicle, it is possible to determine the parking duration, parking times, and the distance to the intersection. Based on this data, the road traffic light situation can be further determined [32].
  For applications that do not require GPS, this can be done with the help of special vehicles, such as buses. As the trajectory of buses is determined, it is easy to determine the traffic status based on the travel time and speed. Passengers or drivers can report the information of connected surrounding base stations to analyze the arrival time of buses.
- **Infrastructure Management**: Here, parking management can be carried out through vehicles. Real-time parking space sensing is carried out through sensors preinstalled on vehicles, which makes parking space monitoring convenient and flexible. In daily scenarios such as queuing at gas stations, real-time queuing status feedback can be provided through vehicle sensing, thereby reducing queuing time. In addition, vehicles can also monitor the health of the bridge through onboard sensors. In disaster scenarios, flexible aviation equipment such as UAVs has a wider range of application scenarios [33].

3) Practical Applications: In 2022, Huawei and China Electronics Standardization Institute jointly released the OpenHarmony-based "White Paper on Urban Sensing System". The white paper describes the urban full-sensing system based on OpenHarmony for the era of full-scenario, full-connection, and full-intelligence. At present, the urban sensing system has also brought new value in application scenarios such as urban public safety, public facilities and public services.

- In terms of urban public safety, such as the maintenance of comprehensive utility corridors. Compared with the construction of traditional underground pipeline network, there are higher requirements for equipment maintenance and inspection in the pipeline gallery. By introducing the OpenHarmony system into the device, a single device can be connected to control multiple devices. It can maximize the help of inspection personnel in the corridor, thereby significantly improving the efficiency of inspection and maintenance of equipment in the corridor.
- In terms of urban public facilities, smart light poles are currently playing an essential role in constructing smart cities. However, it also faces problems such as different interfaces and different protocols of different system terminals, making it difficult to access data and unify integration construction. With the smart light pole as the carrier, the urban components are monitored by installing the sensor equipment of the OpenHarmony system. This can enable devices to perform interconnection and service collaboration near the end.
- In terms of urban public services, the smart parking system is based on OpenHarmony distributed soft bus technology. Therefore, functions such as connecting barrier gates, video terminals, charging piles, display screens, voice intercoms, and detector equipment can be realized. In this way, services such as urban intelligent parking,

on-site guidance, on-street parking, and traffic guidance can be realized. Furthermore, it provides services for car owners' smart travel and parking navigation, thereby improving the efficiency of urban governance.

The above application scenarios are just a "miniature" of the urban sensing system enabling precise sensing and refined governance of smart cities. In addition, it can also play more roles in scenarios including gas safety monitoring, smart environmental protection, natural disaster risk monitoring, high-altitude parabolic monitoring, smart lighting, and smart construction sites. These crowd-sensing-based applications further enhance the efficiency of urban governance and serve the development of smart cities.

D. Related Technologies

In this subsection, we classify and summarize the leading technologies applied in crowdsensing, divided into the following four categories. Fig. 5 shows the classification of relevant technologies in this survey. In addition, Section III and Section IV describe the corresponding technical applications under different sensing entities in detail.

Obviously, mathematics and operations research methods are the most basic optimization methods. It is widely used to solve various practical optimization problems. Of course, it has also been used by researchers to solve problems in sensing scenarios. Common methods include greedy algorithms, matching algorithms, dynamic programming, heuristic algorithm, etc.

In recent years, with the complexity of the problem scenarios, traditional mathematical methods may be difficult to handle. As most problems are NP-hard, traditional mathematical methods can be time-consuming and have high complexity. This creates unnecessary time and cost overhead, while making it difficult to obtain optimal solutions. With the development of AI, various ML methods have been applied in crowdsensing to solve various complex optimization problems. The data training process can be accelerated through various ML methods, and the solution can be solved quickly. Meanwhile, it is equally easy to process large amounts of sensing data.

It cannot be ignored that there is a time or economic cost for participants to perform sensing tasks. As most participants are selfish and rational, it is challenging to perform sensing tasks without reward. Therefore, appropriate rewards are needed to motivate participants to engage in sensing tasks. The incentive mechanisms are mainly introduced from the economics perspective and gradually applied to crowdsensing. At present, the commonly used methods include auction theory, game theory, contract theory, etc.

In the process of crowd sensing, a large number of participants will participate in the sensing task. At the same time, it will also transmit a large amount of sensory data. Therefore, participants' information security and data security issues also need to be considered. Currently, there are various methods to solve the security problem of crowdsensing.

Next, we will introduce the above four technical sectors in detail. Fig. 6 shows the logical relationship between the technologies we have listed.

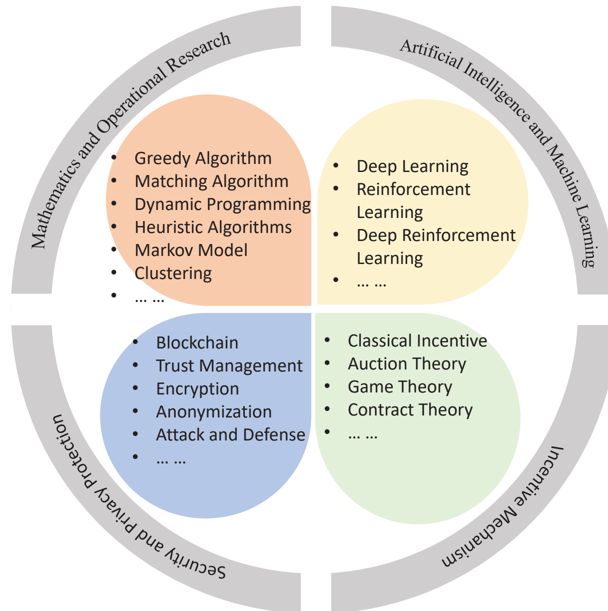

Fig. 5. The classification of related technologies to crowdsensing.

[Mathematics and Operational Research]

1) Greedy Algorithm: The greedy algorithm is one of the most widely used methods. The idea of greed is always to make what seems to be the best choice when solving a problem. In other words, the algorithm obtains a locally optimal solution without considering the overall optimization of problems. Although the greedy algorithm cannot always obtain the optimal solution to the problem, the focus is on selecting the greedy strategy. The idea of greed can be used in solving problems related to crowdsensing, such as participant selection and sensing task allocation [34], [35].

2) Matching Algorithm: The matching algorithm is a prevalent optimization approach that establishes a stable matching relationship between two parties. Specifically, numerous sensing tasks must be stably matched with numerous participants to ensure comprehensive task execution [36], [37].

3) Dynamic Programming: For complex problems, dynamic programming can decompose it into smaller sub-problems that can be solved iteratively. The sub-problems are first solved, then the solution of the original problem is obtained from the solutions of these sub-problems. Certain articles apply the idea of dynamic programming to solve sensing problems [38], [39].

4) Particle Swarm Optimization: Particle Swarm Optimization (PSO) is a random search algorithm that simulates natural biological activities. It searches for the optimal solution through cooperation and information sharing among individuals. It has the property of achieving simplicity, high accuracy and fast convergence. The PSO algorithm demonstrates its effectiveness in solving sensing problems [40], [41].

5) Genetic Algorithm: Genetic algorithm is a computational model that simulates the process of biological evolution by natural selection. It is also the genetic mechanism of Darwin's theory of biological evolution. The genetic algorithm finds the optimal solution by simulating the natural evolution

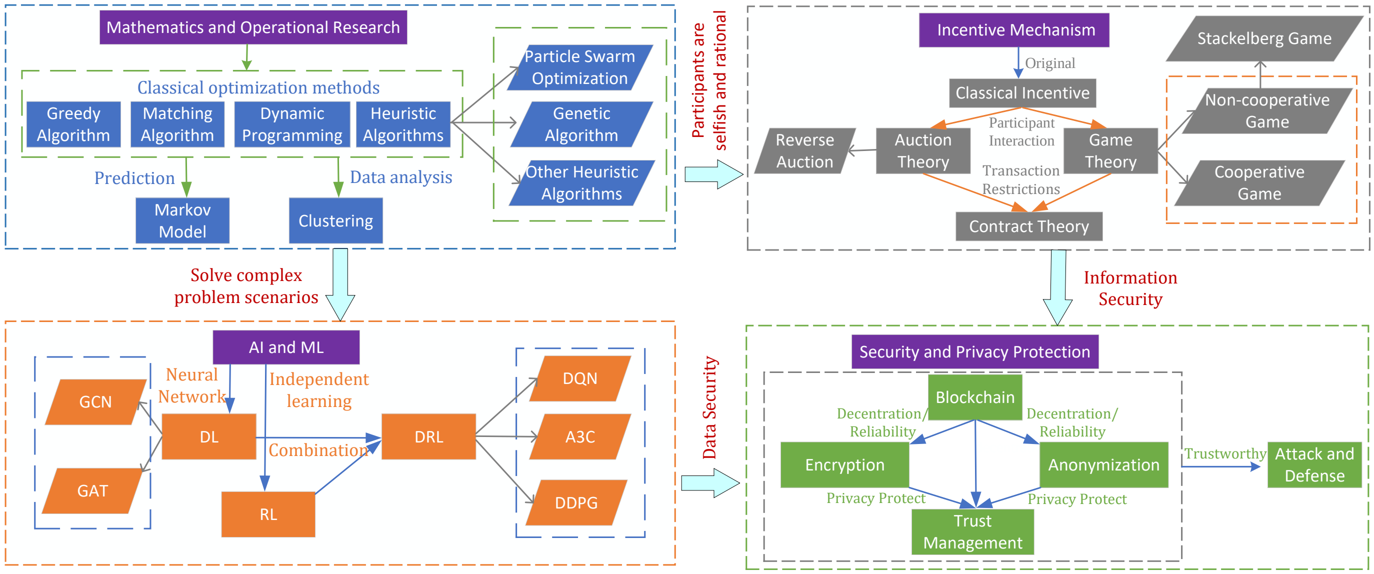

Fig. 6. The relation of technologies applied to crowdsensing.

process. The core concepts of algorithm draw on evolutionary concepts such as heredity, mutation, natural selection, and hybridization. Through these concepts, genetic algorithms can be used to solve optimization problems [42], [43].

6) Other Heuristic Algorithms: Heuristic algorithms are proposed relative to optimization algorithms and are constructed based on intuition or experience. It gives feasible solutions to combinatorial optimization problems within acceptable overhead (time and space). Common heuristics are mainly natural body-like algorithms, such as ant colony algorithms and simulated annealing methods. Many articles apply the idea of heuristic algorithms to solve optimization problems. The corresponding heuristic method is formulated according to the required solution problem, and the approximate ratio of the algorithm can be guaranteed [44], [45].

7) Markov Model: The Markov model is a statistical tool with applications in numerous domains. It encompasses several concepts, such as Markov chain, semi-Markov chain, Markov prediction, etc. In fact, as a concept derived from probability theory and mathematical statistics, the Markov model has been developed into a method to predict the probability of events. In addition, the Markov model is also applied to various ML methods. Many researchers have applied Markov-based methods to predict future situations. For example, the trajectory of next moment is predicted according to the vehicle history trajectory information [46], [47].

8) Clustering: Clustering is a multivariate statistical analysis method. Its function is to classify a large amount of data according to similarity. Objects in the same class are as similar as possible, while objects in different classes are as different as possible. Typically, for many PoI (Points of Interest) scenarios, it is possible to classify them by clustering methods. In this way, only a few participants are required to perform sensing tasks at many PoIs. The clustering analysis derived from the clustering idea is also applied in the field of ML [48], [49].

[AI and ML]

1) Deep Learning (DL): DL is a research direction in the field of ML, and it is also one of the most widely used methods at present. Through the neural network structure to achieve complex function approximation, DL can discover the distributed characteristics of data. It also demonstrates the powerful ability to learn the basic features of datasets from small samples. Currently, the commonly used DL models include Convolution Neural Networks (CNN), Recurrent Neural Networks (RNN), etc. Here, we will also introduce the following two neural networks:

- Graph Convolutional Networks (GCN): GCN is a convolutional neural network that can directly act on a graph and use its structure information. In other words, GCN actually does the same thing as a CNN - it is a feature extractor, except that its object is graph data. GCN is a cleverly designed method for extracting features from graph data to classify and process the graph data [50].
- Graph Attention Networks (GAT): GAT is a new neural network architecture based on graph-structured data, which is actually a combination of GCN and attention mechanisms. It uses a hidden self-attentive layer to address the shortcomings of previous approaches based on graph convolution or its approximations [51].

Researchers have applied the above neural network model to solve specific problems related to crowdsensing.

2) Reinforcement Learning (RL): RL is also a branch of ML that relies on feedback signals from individuals (agents) in the environment. RL corrects the individual's state and actions based on the feedback signals, allowing the individual to maximize the reward progressively. As mentioned above, RL typically includes four elements: policy, reward, value, and environment (model):

- Policy: Policy defines the behaviour of an agent in a given state. In other words, it is a mapping from state to behaviour, and the state includes the environment and agent states.

- Reward: Reward defines the goal of RL problems. In each time step, the scalar value sent by the environment to RL is the reward, which defines the agent's performance. The reward is the main factor affecting the strategy. The agent aims to maximize the total reward value accumulated over time.
- Value: Unlike the immediacy of the reward, the value function measures long-term benefits. It evaluates the benefits of the current behaviour from a long-term perspective and also evaluates the quality of state.
- Environment: The external environment, or model, is a simulation of the environment. When the model gives states and behaviours, it is possible to predict the next state and the corresponding reward. It should be noted that several methods are model-free, which learn by analyzing policy and value functions.

The most basic RL method is Q-learning. In Q-learning, the agent makes corresponding actions in the current state and receives corresponding rewards, then turns to the next state. The goal is to maximize the overall return [52].

3) Deep Reinforcement Learning (DRL): Typically, traditional RL methods perform poorly on high-dimensional state-action space tasks due to using the Q-table method to evaluate value functions. Therefore, DL has been introduced recently. The learning ability of deep neural networks can solve problems that are too complex for the classical RL method. At present, many DRL methods have been applied in the field of crowdsensing to solve a large number of complex problems. We briefly summarize several of these methods:

- Deep Q-learning (DQN): DQN is an improvement of Q-learning. Its Q-value is not calculated directly by state value and action but by the Q-network, which is actually a neural network. Based on DQN, many improved versions are developed, such as Double DQN (DDQN), Prioritized Replay DQN, and Dueling DQN [53].
- Actor-Critic (AC): AC method is a combination of strategy and value. The Actor uses the policy function to generate actions and interact with the environment. The critic uses the value function to evaluate the Actor's performance and guide the Actor's actions in the next stage. In fact, the results obtained by the AC method are difficult to converge, so many methods are derived to solve this situation [54].
- Asynchronous Advantage Actor-Critic (A3C): A3C uses a multi-threaded learning approach by simultaneously interacting with the environment in multiple threads. Each thread summarizes the interactive data and stores it in the global network. Furthermore, the data is regularly updated from the global network to guide its own learning interactions with the environment. In this way, A3C avoids the problem that AC may cause difficulty in convergence due to excessive experience playback, and realizes asynchronous concurrency. [55].
- Deep Deterministic Policy Gradient (DDPG): Unlike A3C, DDPG uses experience replay and a dual-network approach to improve the hard-to-converge AC problem. DDPG continues the idea of DQN target network. Each Actor and Critic network is subdivided into the target and current networks. The difference lies in the update method of target network [56].

[Incentive Mechanism]

1) Classical Incentive: The most basic used incentive method is monetary reward. The platform can provide fixed unit rewards based on task completion. Furthermore, in addition to fixed monetary rewards, several studies have introduced the concept of floating rewards. In this way, participants are motivated to compete for more significant gains for completing high-quality sensing tasks. Specific pricing strategies are analyzed on a case-by-case basis in different articles. These pricing strategies will be discussed in detail later [57], [58].

2) Auction Theory: The reverse auction is one of the most commonly used incentive methods. Generally, the auction is made by the seller, and the specific buyer is determined by strategy. Obviously, reverse auctions turn this process around. The buyer bids the reverse auction, and the seller decides its own strategy according to the corresponding bid. Reverse auctions are widely used between the platform and participants. The main objective is to minimize platform costs and maximize participants' benefits. Generally, there are two steps in a reverse auction: the selection of winner, and the determination of pricing strategy. The platform selects which participants will perform the task based on their bids and then determines the specific bidding strategy. In addition, online reverse auction and offline reverse auction are also distinguished in several studies [59], [60].

3) Game Theory: Game theory is a mathematical model based on economic theory, which is mainly used to solve the interaction problem between rational participants. It is mainly divided into the cooperative game (coalitional game) and the non-cooperative game. The game model is mainly divided into three parts: player, action (strategy), and utility. Generally, the game process will reach an equilibrium state called Nash Equilibrium (NE) [61].

The most classical model in game theory is the Stackelberg game. The Stackelberg game divides participants into leaders and followers. The leader first gives the strategy, and followers determine their own strategy according to the leader's strategy. The ultimate goal of all participants is to maximize their own benefits. According to the number of leaders and followers, Stackelberg Game can be divided into the one-to-one game, one-to-many game, and many-to-many game. Similarly, the final equilibrium state of the Stackelberg game is called the Stackelberg equilibrium. Fig. 7 shows the basic process of Stackelberg game [62].

4) Contract Theory: Contract theory is also a branch of economics, which has gradually developed into a mathematical model. Contract theory regards all transactions or interactions as contracts. During the interaction between participants, it is necessary to observe the agreement of both parties. Therefore, the contract theory is more complex than the preceding incentive methods [63], [64].

[Security and Privacy Protection]

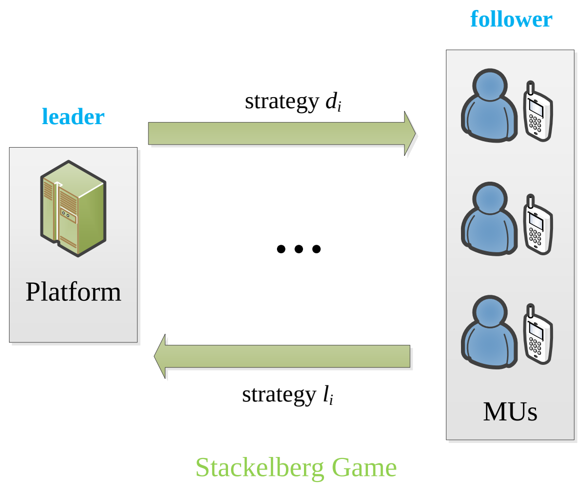

Fig. 7. The basic Stackellberg game process.

1) Blockchain: Blockchain is a distributed data storage technology. Blockchain enables secure transactions through a decentralized network of nodes that record transactions in blocks. In addition, it supports using encryption techniques to defend against malicious attackers. Using blockchain technology, sensing data or participant information is stored on the block to prevent malicious access. At the same time, as one of the cores of blockchain technology, the application of smart contracts can ensure the safety and reliability of decentralized transaction systems [65], [66].

2) Trust Management: Trust is generally divided into two types: identity-based trust and behaviour-based trust. Identity-based trust uses a static control mechanism that restricts access to the target object until the user performs access to the object. Behaviour-based trust dynamically judges the credibility of target entity through the entity's behaviour history and current behaviour characteristics.

Participant safety has acquiesced in most studies. In fact, many malicious participants will destroy the integrity of the crowdsensing system. For example, deliberately submitting wrong sensing results, malicious bidding to disrupt the trading market, etc. In addition, many sensing tasks require the collaboration of multiple participants to complete. Since the participants are strangers, they cannot trust each other. Therefore, the current reputational value of participants can be assessed through their historical behaviour. Participants with lower reputations will be restricted from performing sensing tasks [67], [68].

3) Encryption: Encryption is a method of converting information into a password that hides the true meaning of information. Data privacy can be effectively protected by changing the original data information using a specific method. Common encryption methods include key hashing, symmetric encryption, asymmetric encryption, digital signature, etc. Although these encryption methods have different processes, they aim to protect data security [69], [70].

4) Anonymization: Anonymization technology is also a technical means of privacy protection. Data anonymization can be used to protect private information. It can be achieved by removing links between individuals and stored data, or by encrypting relevant identifiers. Common anonymization technologies include k-anonymity, L-diversity, T-closeness, differential privacy, etc [71], [72].

5) Attack and Defense: Nowadays, many malicious individuals attack platforms and participants, or the corresponding networks and data, threatening the crowdsensing process. Therefore, the corresponding defence measures are particularly important. Common defence techniques include intrusion detection, firewalls, access control, etc [73], [74].

[Others]

This category includes parts that have not been specifically classified before, but remain focused on specific areas. Several studies have applied data structures to solve sensing-related problems. The most used are graph and tree structures.

- Graph is a complex nonlinear data structure, which is usually used to represent the many-to-many relationship. In the field of crowdsensing, graph structures have many applications. A subset of path planning problems involves converting road information into a graph and solving for the shortest path. The weight on the edge can be thought of as distance or cost. In addition, graphs can represent dependencies between sensing tasks or social relationships between participants [75], [76].
- Tree is a non-linear data structure that can be viewed as a graph without the ring. The tree is mainly used to represent the hierarchical relationships between nodes. For example, the spatiotemporal information of sensing tasks can be transformed into a tree, and the task can be executed in chronological order by depth-first traversal [77], [78].
- In several scenarios, each participant will be assigned with multiple tasks involving the execution order. Generally, the queue can be applied to store sensing tasks that have not yet been executed, and then execute tasks in the first-in-first-out order [79].

III. Human-oriented sensing

This section first introduces the basic framework of crowdsensing. Then, issues tackled by relevant studies on human-oriented sensing are summarised. Furthermore, these relevant studies are categorized and analysed from a technical perspective. Finally, we elaborate on specific application scenarios for crowdsensing. Fig. 8 shows the structure of this section.

A. The Framework of Crowdsensing

The successful implementation of crowdsensing requires cooperation from multiple parties and involves multiple steps. As mentioned earlier, the main participants in the crowdsensing system include task publishers, platforms, and task performers. Meanwhile, as illustrated in Fig. 9, the following steps are necessary for implementing sensing tasks:

- **Task publishing**: The task publisher generates the sensing task and uploads relevant information to the platform. This information includes time and location constraints,

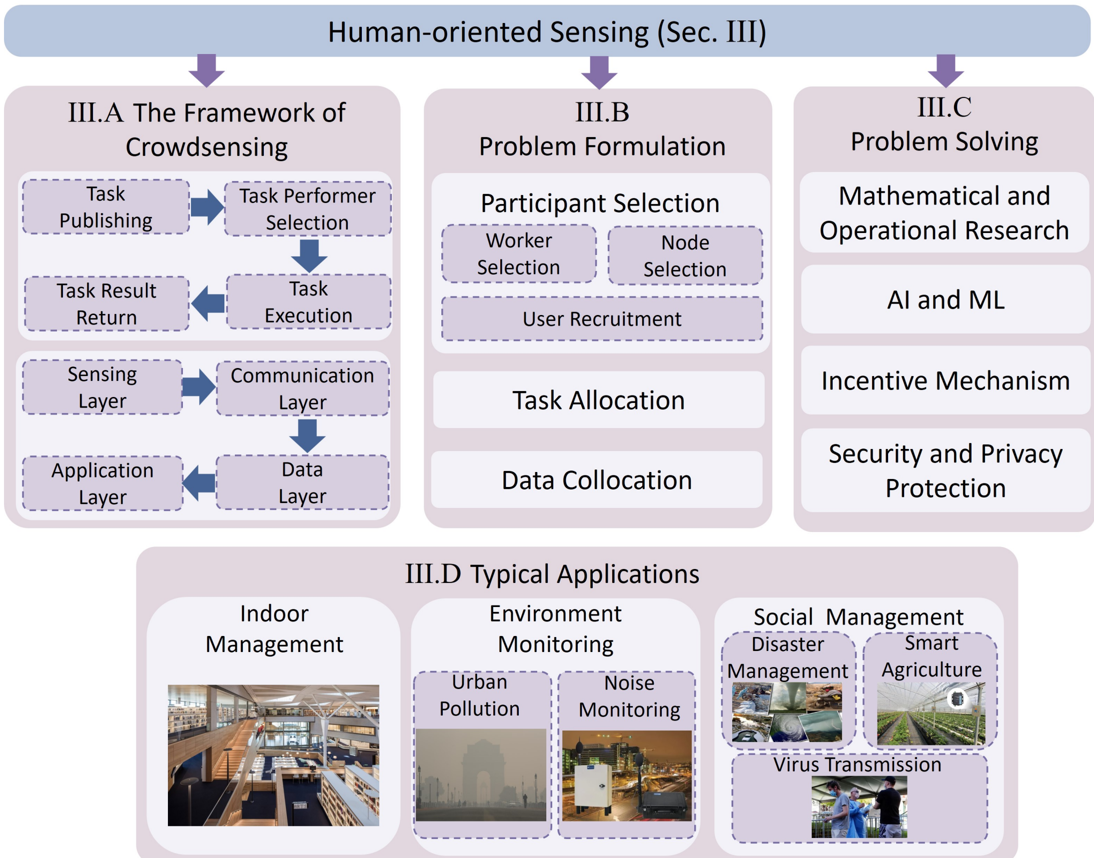

Fig. 8. The structure of section III.

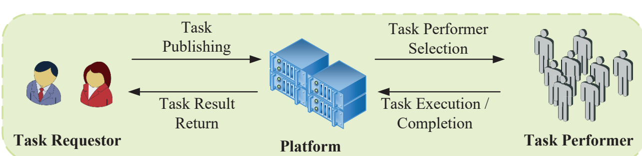

Fig. 9. The step of the crowdsensing process.

required sensing abilities, the amount of sensing data, and the reward, etc.

- **Task performer selection**: Performers interested in participating in sensing tasks need to provide their information to the platform. Based on the requirements of the task publisher, the platform selects the most suitable performer to implement the task within a specific period.
- **Task execution**: The selected performers diligently carry out the sensing tasks assigned by the platform. Meanwhile, task performers may adjust their strategies to pursue higher rewards.
- **Task completion**: Once the task is completed, the performer uploads the collected data to the platform, and the platform awards the corresponding reward based on the quality of the collected data.
- **Task result return**: After processing the data, the platform sends the results to the task publisher. Correspondingly, the publisher pays the task completion fee to the platform.

Based on the stages involved in task execution, the architecture of the crowdsensing system is divided into four layers: sensing layer, communication layer, data layer, and application layer, as shown in Fig. 10.

1) Sensing Layer: The sensing layer serves as the foundation of crowdsensing. It is responsible for acquiring sensing data through various sensors and IoT devices. Typically, implementing sensing tasks relies on MDs carried by MUs. Different sensing task types may necessitate the use of GPS, WiFi transmitters, Bluetooth, cameras, and other specialized sensors (air quality sensors, noise sensors, etc.). These sensors are connected to the MD, and collected data is transmitted to the platform through the communication capability of MDs.

2) Communication Layer: The communication layer is responsible for the data transmission. The data collected by MDs is typically transmitted wirelessly, either through WiFi connections or cellular networks. Since data is the focal point of crowdsensing, ensuring secure and reliable data transmission is paramount. Besides, the transfer rate must be optimized to avoid redundancy. Specifically, measures include efficiently utilizing available bandwidth, enhancing signal strength, and adopting appropriate protocols.

3) Data Layer: The data layer is dedicated to analyzing and processing collected sensing data. Different tasks generate diverse data types, necessitating the platform to possess robust computing power for handling. In addition, the platform is

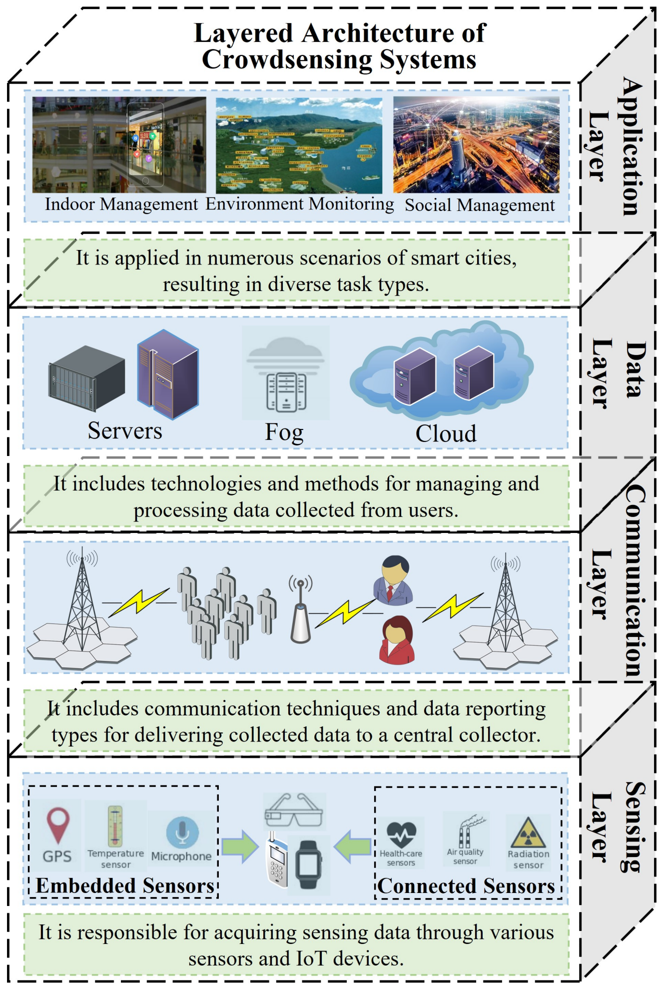

Fig. 10. The architecture of the crowdsensing system.

pivotal in the data layer and encounters significant security challenges. As the data custodian, the platform must ensure data integrity, confidentiality, and protection against unauthorized access.

4) Application Layer: The application layer mainly revolves around published tasks. Crowdsensing has been applied in numerous applications in smart cities, resulting in diverse task types. Therefore, designing suitable task allocation and participant recruitment methods becomes crucial to successfully implementing these tasks.

B. Problem Formulation for Human-Oriented Sensing

In human-oriented sensing processes, several significant challenges need to be addressed. For instance, selecting the most suitable task performer from the participant pool, assigning sensing tasks to optimize completion rates, and ensuring high-quality data collection for sensing tasks. Recently, researchers have devoted their efforts to tackling these challenges and have proposed various solutions. Table III categorizes the relevant research around problems and solutions.

1) Participant Selection: Participant selection significantly impacts various aspects of following research in crowdsensing. Indeed, this selection problem encompasses several subproblems, such as worker selection, user recruitment, and node selection. Despite these sub-problems enabling different perspectives, the ultimate objective remains: identifying and selecting the most suitable participants for the sensing task.

Worker Selection: Related research efforts treated participants as workers. This stems largely from the concept of crowdsourcing, which relies on widespread MDs of workers to perform sensing tasks. The task implementation mainly depends on the ability and effort of these workers. To ensure task coverage and maintain a balanced distribution, Wang *et al.* in [80] explored worker selection in spatial crowdsourcing with a dynamic programming method. Their goal was to recruit appropriate workers while keeping labour expenditures to a minimum. Similarly, in [81], a dynamic budget allocation mechanism was proposed to optimize worker selection. They considered bias and variance as two variables to measure task continuity, and modelled them to estimate worker quality.

The issue of worker selection is also posed in other different sensing settings. Based on a fog platform, Yang *et al.* in [82] tackled the worker selection problem with an online learning method. They recorded historical data of workers on fog servers and selected the most suitable workers based on the historical information. The objective is to maximize the long-term utility of the platform under budget constraints. In [83], Lu *et al.* presented the challenge of selecting the least number of workers to enhance task execution efficiency. They designed a multi-objective worker selection problem with constraints, and obtained the optimal solution via a differential evolution method. Furthermore, in [84], Li *et al.* explored selecting suitable workers from a large pool of candidates. Based on the correlation between workers, they proposed a context-aware solution to maximize sensing benefits.

User Recruitment: User recruitment involves attracting potential participants to complete sensing tasks in the absence of candidates. In [85], the corresponding user recruitment problem was formulated as integer linear programming. Authors presented two user recruitment strategies based on four criteria. One relied on the experience of the platform, while the other leveraged the social relationships of users. Wang *et al.* in [86] conducted personalized user recruitment with the consideration of user preferences. They predicted matching rates between users and tasks by binary classification, and selected the worker with the highest matching rate. Gao *et al.* in [87] proposed a credible user recruitment mechanism to fulfil the optimization objectives. It considered user reliability based on historical information submitted by users, and maximized the benefits for both users and the platform under budget constraints. Moreover, in [88], Zhang *et al.* investigated the edge-assisted dynamic user recruitment problem. Here, a simple static scenario is studied, and a static user recruitment method is proposed. Then, the complex dynamics are considered, and a multi-armed bandit-based method is proposed.

Node Selection: Node selection generally occurs in trust management and privacy protection. It involves determining the trustworthiness of participants and selecting suitable ones based on it. In [89], Zhao *et al.* proposed a trusted node selection method. They assessed the trust value of each node based on factors (node location, sensing capability, etc.). Based on these factors, suitable nodes were selected to participate

TABLE III
PROBLEM FORMULATION FOR HUMAN-ORIENTED SENSING

Pro.	Type			Ref.	Objective	Approach	Restrictions
Participant Selection	Worker Selection	Crowdsourcing worker		[80]	Minimize the costs paid to workers	Dynamic programming	Ensure task coverage + Ensure balanced coverage
				[81]	Choose the most reliable workers	Dynamic budget allocation method + Multi-armed bandit algorithm	Limited budget
		Crowdsensing worker		[82]	Maximize the long-term utility of the platform	online learning method	Budget constraint
				[83]	Improve the efficiency of sensing task completion	using the differential evolution method	Budget constraint
				[84]	Maximize sensing benefits	Context-aware worker selection algorithm	Budget constraint + Capacity constraint
	User Recruitment			[85]	Recruit the optimal team	Integer linear programming problem	——
				[86]	Select the highest matching rate worker	user recruitment mechanism	Workers' preference constraint
				[87]	maximize the benefits of users and the platform	semi-Markov model + Game theory	Budget constraint
				[88]	Maximize tasks' completion ratios	Edge-node user recruitment algorithm + Combinatorial multi-armed bandit	Delay sensitive + Budget constraint
	Node Selection			[89]	Select suitable nodes	Cross-domain collaborative filtering method	Trust value constraint
				[90]	Minimum crowdsourcing cost	The branch and bound method	Under both reliability and cost requirement
				[91]	Reduce time consumption + better privacy protection effect	A lightweight privacy-preserving node selection algorithm	——
Task Allocation	Independent Tasks	Participant Independence	Offline	[92]	Maxmize the total rationality of sequences	Greedy method	Task priority and task similarity
				[93]	Efficiently complete sense tasks	Multivariate Gaussian process update algorithm + Map-based self-repair task assignment algorithm	——
				[94]	Reduce the task compeletion cost	Heuristic algorithm	Budget constraint
				[95]	Collect high-quality sensing result	particle swarm optimization-based method	Time constraint
			Online	[79]	Meeting the requirements of tasks and participants	Dynamic matching method + Tree structure	——
				[96]	Maximize the benefits of participants	Multi-agent RL algorithm	Location familiarity constraint
				[97]	High-quality data collection	Unsupervised learning method + Online task allocation scheme	Location constraint
			Both online and offline	[98]	Maximizing platform profits	Ant colony algorithm + Online algorithm	Task deadline
				[99]	Balancing user sensing costs	Polynomial-time algorithm	Meet data quality requirements
				[100]	Maximize the overall system utililty	Descent greedy approach	Number of tasks for workers + Sensor availability
		Participant collaboration		[101]	Maximize the utility of task execution	Auction-based incentive mechanism	Fair distribution of tasks
				[102]	Improve the task coverage and task cooperation quality	Heuristic algorithm	——
				[103]	Minimize the sensing cost	Reverse auction-based incentive mechanism	——
	Splittable Tasks			[104]	Maximize the sensing capacity of users	Optimized allocation scheme of time-dependent tasks	Time constraint
				[105]	Minimize the cost of the platform + Maximize task coverage	Greedy-based method	Time and location constraint
				[106]	Select suitable participants to collecte sensing data	Game theory + Distributed approximation method	——
				[107]	Improve task coverage	Worker recruitment framework based on edge-cloud collaboration	Time and cost constraint
	Interdependent Tasks			[108]	Minimize task completion time	Graph scheduling + Heuristic algorithm	Task dependency
				[109]	Imporve efficient task allocation	Greedy-based + Game theory-based methods	Task dependency
				[110]	Maximize the system's effectiveness	Greedy descent method	Sensing quality threshold + Task dependency
				[111]	Ensure the task completion rate	Depth-first search + Dynamic task allocation algorithm	Task dependency
Data Collocation	——			[112]	Improve data quality + Profit maximization	Bayesian inference + Incentive mechanism	——
				[113]	Improve sensing quality of works	Game theory + Truth discovery algorithm	——
				[114]	Improve data quality	Incentive mechanism + Heuristic algorithm	Users influence
				[115]	Reliable data collection	Expectation-maximization-based approach	——
				[116]	Maximize social utility	Incentive mechanism	Users uncertainty

in the sensing task. Similarly, authors in [90] formulated the trusted node selection problem as an inverse knapsack problem. The branch and bound method were employed to identify the trusted node with the minimum crowdsourcing cost. Furthermore, as for privacy concerns, authors in [91] proposed a privacy-preserving node selection scheme with blockchain. They established a distributed sensing framework to protect the node selection process. This approach not only guarantees result accuracy but also reduces time costs.

2) Task Allocation: Sensing task allocation is a widely studied topic among researchers. By efficiently assigning sensing tasks, the task execution rate and execution cost can be improved. Generally, there are two main strategies for task allocation: centralized and distributed. In the centralized strategy, the platform makes decisions and assigns tasks to suitable participants. In contrast, the distributed strategy allows participants to make decisions and match themselves with tasks. Furthermore, researchers have delved into classifying sensing tasks in great detail (for example, indivisible/divisible

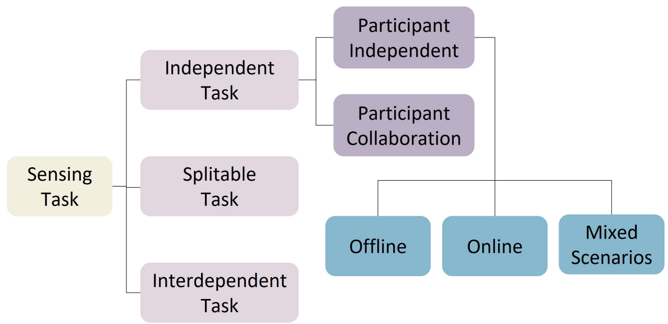

Fig. 11. The classification of sensing task allocation.

tasks, tasks with dependencies, etc.). Different task types give rise to various challenges and problem formulations. In the following, we will elaborate on the classification of task types. Specifically, independent, splittable, and interdependent tasks are discussed. The classification of this part is shown in Fig. 11.

- **Independent Tasks**: Independent tasks, which are mutually independent and inseparable, have been the most frequent setting in this field. In such cases, most studies concentrate on the allocation process between tasks and MDs, without explicitly considering the impact of task constraints. Besides, it is worth noting that while tasks are independent, certain studies argue against the one-to-one matching relationship between tasks and users. These above considerations undoubtedly increase the complexity of the problem.
  Partial studies in crowdsensing focus on independent sensing tasks. Authors in [92] proposed a task allocation problem that considers task similarity and priority. Their objective is to assign tasks to a group of workers and generate an appropriate task sequence. In [93], the task allocation problem in a multi-agent crowdsensing system was considered. An information map-based allocation method was proposed to assign suitable tasks to heterogeneous robots. In [94], the authors focused on assigning and scheduling tasks for workers. By optimizing the location of workers, the task allocation cost was reduced through two heuristic algorithms. In [95], a task allocation problem with time constraints was formulated. Authors proposed a particle swarm optimization-based method that considers the task locations. Moreover, the scenario in which the task cannot be performed was considered, and the task will be reassigned to eligible workers.
  Other studies focus on scenarios where multiple participants collaborate to complete a task. Luo *et al.* in [101] emphasized that tasks require a group of users to work together and necessitate a fair distribution of them. They considered the potential for user cooperation and proposed an auction-based incentive mechanism. To solve the group-oriented cooperative crowdsensing problem, Tan *et al.* in [102] proposed a three-stage approach for task allocation. Specifically, users are divided into different groups, and social relationships among them are assessed based on their leaders. Similarly, Xu *et al.* in [103] grouped users via clustering techniques in the exact scenarios. They designed a reverse auction-based incentive mechanism to motivate each group to perform tasks, with the goal of minimizing sensing costs.
- **Splitable Tasks**: Partial studies suggest that sensing tasks can be divided into multiple subtasks and executed by different participants. In [104], authors focused on task allocation in time-dependent crowdsensing systems. They proposed an optimal allocation scheme for time-dependent tasks, considering the user's sensing duration and ability. Ma *et al.* in [105] addressed the execution of heterogeneous tasks, which can be divided into multiple subtasks. To minimize the platform cost and maximize task coverage, they formulated a heterogeneous user recruitment problem, and proposed three greedy-based methods to obtain approximate optimal solutions. In [106], authors explored the scenario where multiple users are assigned to complete a subtask jointly. To assign tasks to suitable participants, they proposed a game-based dynamic participant selection framework and a distributed approximation method. Zhu *et al.* in [107] considered the framework of edge-cloud collaboration. The sensing area was partitioned into small grids according to task position by the cloud, while a mathematical model was constructed to make decisions on worker recruitment at the edge.
- **Interdependent Tasks**: Sensing tasks can not only be divided into multiple subtasks but also have dependencies between them. Wang *et al.* in [108] considered this complicated situation where subtasks have dependencies. They modelled the task dependencies as a directed graph and transformed the task allocation problem into a graph scheduling problem. In [109], Liu *et al.* investigated a multi-stage complex task allocation problem considering task dependencies. They proposed greedy-based and game theory-based methods for more efficient task allocation. In [110], Wang *et al.* introduced a sensing quality threshold with considering the dependencies between subtasks. They proposed a greedy descent-based task allocation framework to maximize the effectiveness of the system. Furthermore, based on the dependencies between subtasks, Yang *et al.* in [111] formulated the task allocation problem and ranked the subtasks based on their dependencies using a depth-first search.
  The above studies on task allocation primarily focus on static scenarios (i.e., offline scenarios, where users and tasks are predetermined and the platform shares global information.). In contrast, recent studies attempt to explore complex dynamic scenarios (i.e., online scenarios, where users and tasks participate in the sensing process anytime, and the platform only has knowledge of the current state.). In [79], authors addressed the problem of online heterogeneous task allocation. They utilized data structures to transform the spatiotemporal characteristics of tasks into a tree, and created temporal queues to organize participants based on their dynamic properties. Chen *et al.* in [96] tackled the online sensing task allocation problem from the perspective of participants.

The problem was formulated as a multi-agent Markov decision process, with the corresponding objective being to maximize the benefits of participants. In [97], Wang *et al.* considered online location-based sensing. To ensure high-quality data collection and task execution, they proposed an unsupervised learning method and designed an online task allocation scheme.

In addition, several studies have explored both offline and online scenarios. In [98], authors investigated the task allocation problem considering spatiotemporal characteristics. They proposed an ant colony algorithm to obtain an approximate optimal solution in the offline scenario. Meanwhile, several algorithms that utilize historical information of workers were developed in the online counterpart. Sun *et al.* in [99] proposed a cost fairness-oriented sensing task allocation problem in offline and online scenarios. Their objective was to balance the cost among users while meeting the data quality requirements through task assignment. Wang *et al.* in [100] introduced a framework called HyTasker for sensing task allocation. They selected opportunity workers to complete daily sensing tasks offline, and participatory workers to handle the remaining tasks online.

3) Data Collocation: Besides selecting appropriate participants and effective task allocation strategies, evaluating task completion is also crucial in crowdsensing. Several studies are based on the quality of the collected sensing data. Peng *et al.* in [112] introduced a compensation mechanism where participants are paid based on the quality of the collected sensing data. This mechanism can avoid low-quality data and additional cost consumption effectively. Jin *et al.* in [113] attempted to enhance the sensing quality of workers in both complete and incomplete information scenarios. They incentivized workers to execute high-quality sensing, and proposed a game theory-based payment mechanism to determine the decisions of workers. Furthermore, Gao *et al.* in [114] considered the data quality and incentive mechanisms jointly. They selected suitable participants based on the influence of users, and provided compensation based on the data quality. Wang *et al.* in [115] investigated reliable data collection in the Device-to-Device (D2D) scenario. They formulated the data reliability as a probability problem, and proposed an expectation maximization-based solution. Zhang *et al.* in [116] designed an incentive mechanism to achieve high-quality data collection, where their objective is to maximize social utility.

C. Problem Solving and Strategies for Human-oriented Sensing

In Section II-D, we have classified and elaborated on the relevant technologies applied in crowdsensing. This subsection summarizes relevant literature which applies these techniques in human-oriented sensing.

[Mathematics and Operational Research]

Research works related to applied mathematics and operational research includes the greedy algorithm [34], [117], [118], the matching algorithm [36], [37], [119], [120], dynamic programming [38], [121], [122], particle swarm optimization [123], [40], [124], the genetic algorithm [42], [43], [125], other heuristic algorithms [44], [126], [127], Markov Model [46], [128], [129], and clustering [48], [130], [131]. The summary and organization of these studies are listed in Table IV.

1) Greedy Algorithm: In [34], authors considered geographical relevance and task information. Based on the location sequence generation, several greedy-based algorithms were proposed to tackle task allocation and path planning issues. In [117], authors investigated the impact of worker trajectories on task execution. They presented a greedy-based method to minimize task overhead while considering task completion time and budget factors. Li *et al.* in [118] explored task allocation in opportunity-based crowdsensing. They proposed a greedy-based online algorithm and a multi-stage allocation strategy to minimize the task completion time.

2) Matching Algorithm: To ensure the efficient execution of sensing tasks by workers, several studies explored stable task-matching strategies. Dai *et al.* in [36] developed a many-to-many matching model between independent sensing tasks and users. They designed a stable matching algorithm to allocate the tasks to the users and determine their payments. Similar to [36], Yang *et al.* in [37] formulated a multi-objective problem to achieve stable task matching in the presence of worker competition. They proposed a game-based method to determine worker strategies, and designed a stable matching method for task allocation. By exploiting the spatiotemporal properties of workers, Wang *et al.* in [119] constructed an assignment graph, and designed a population-based optimization method to ensure robust task allocation. Furthermore, Yucel *et al.* in [120] investigated the formation of stable task allocation between users and tasks via matching theory. They considered the many-to-one nature of tasks, and proposed three stable allocation methods to achieve high-quality allocation processes.

3) Dynamic Programming: Hu *et al.* in [38] investigated location-based task allocation problems for participating and opportunistic users. They proposed a dynamic programming and backtracking-based strategy to maximize user profits. Gao *et al.* in [121] applied the truth value judgment method to infer worker quality. They transformed the task allocation problem into two sub-problems, which were solved by the Hungarian method and dynamic programming, respectively. Moreover, Li *et al.* in [122] proposed a resource-constrained sensing scheme to optimize sensing performance. Here, they divided the proposed nonconvex optimization problem into internal and external subproblems. The former determined the communication and computing strategy, while the latter determined the user selection strategy.

4) Particle Swarm Optimization: Lou *et al.* in [123] investigated the task allocation problem considering delay and worker capacity constraints. They introduced a particle swarm optimization-based task allocation method, which maximizes social welfare and reduces task costs greedily. Wang *et al.* in [40] explored the heterogeneous task allocation strategy to enhance task coverage and reduce task costs. They proposed multi-objective particle swarm and linear weight optimization

TABLE IV
SUMMERY OF MATHEMATICAL AND OPERATIONAL RESEARCH IN HUMAN-ORIENTED SENSING (PS: PARTICIPANT SELECTION, TA: TASK ALLOCATION, DC: DATA COLLOCATION, MOR: MATHEMATICAL AND OPERATIONAL RESEARCH, IM: INCENTIVE MECHANISM)

Ref.	Problem			Problem Solving		Objective	Restrictions
	PS	TA	DC	MOR	IM		
[34]		X		Greedy algorithm		Generate location-visiting sequences	Task similarity + Task priority
[117]		X		Greedy algorithm		Minimize task overhead	Task completion time and budget
[118]		X		Greedy algorithm		Minimize the task completion time	——
[36]	X	X		Stable task-matching method		Maximizing participant utility	Budget constraint
[37]		X		Stable matching method	Game Theory	Maximize worker satisfaction + Maximize platform benefit	Time constraint
[119]		X		Population-based optimization		minimize the cost of workers	Spatiotemporal constraint
[120]		X		Stable allocation methods		High-quality and stable allocation	——
[38]		X		Dynamic programming + Backtracking-based approach		Maximize user profits	Location constraint
[121]		X		Hungarian method + Dynamic programming		Improve the sensing quality	The quality of workers
[122]			X	Dynamic programming		Maximize task completion	Data transmission + Communication resource limitation
[123]		X		Particle swarm optimization + Greedy method		Maximize social welfare + Reduce task costs	Delay constraints + Worker capacity constraints
[40]		X		Particle swarm optimization + Linear weight optimization		Maximize task coverage + Minimizing task costs	Task probability coverage + Budget constraint
[124]		X		Multi-objective particle swarm optimization		Maximize the utility of participants	Spatio-temporal constraint
[42]		X		Clustering + Genetic algorithm		Maximize the quality of collected data	Geographical distribution
[43]		X		Greedy genetic algorithm		Minimize worker movement distance	Worker actions
[125]		X		Linear programming + Genetic algorithm		Improve tasks completion	Energy constraint
[44]	X			Beetle swarm optimization		Reduce task execution time	Route constraint
[126]	X			Heuristic evolutionary approach	Game Theory	Maximize Platform profit	Time constraint
[127]		X		Heuristic-based polynomial method		Maximize system utility + user satisfaction	Individual preferences
[46]		X		Semi-Markov prediction + Meta-path prediction		Improve tasks completion	Time constraint
[128]	X		X	Markov chain + Task decomposition and subcontract algorithm		Improve the quality of sensing data	Spatiotemporal constraint
[129]		X		Semi-Markov model + Prediction-based allocation method		Improve allocation efficiency + Reduce worker costs	Location constraint
[48]		X		Cluster formation method		Improve worker payoff	Ensure satisfaction with task completion
[130]		X		Greedy + Clustering		Minimize the maximum task span of requesters	——
[131]	X			Clustering		Maximize task coverage	Time and cost constraints

methods to solve the problem. Additionally, Wu *et al.* in [124] considered the multi-objective task allocation in edge computing scenarios. They proposed a weighted multi-objective particle swarm optimization algorithm to maximize the utility of participants.

5) Genetic Algorithm: Tao *et al.* in [42] clustered tasks based on geographic information. They applied genetic and detection algorithms to improve the data collection quality and worker earnings, respectively. Guo *et al.* in [43] introduced a task allocation framework called ActiveCrowd to minimize the distance traveled by workers. To obtain optimal decisions, two greedy genetic algorithms were proposed based on the framework, where intentional and unintentional actions of workers during task execution were considered. In [125], authors considered energy-constrained sensing scenarios, and ensured task completion through the energy balance problem among participants. They proposed a Lyapunov-based energy balance method, as well as a linear programming and genetic algorithm-based task allocation method.

6) Other Heuristic Algorithm: In [44], authors attempted to plan suitable routes for participants to reduce task execution time. They proposed a beetle swarm optimization-based strategy to find the optimal path. In [126], authors designed a price mechanism, where the platform maximizes its profits by determining the perceived strategies of participants. Based on the data freshness measure, they proposed a heuristic evolutionary and a relaxation approach for the information age-sensitive and age-insensitive cases, respectively. In [127], authors considered task allocation based on user preferences. To maximize system utility and user satisfaction, they proposed two heuristic-based polynomial methods for formulated integer linear programming.

TABLE V
SUMMERY OF AI AND ML RESEARCH IN HUMAN-ORIENTED SENSING (SPP: SECURITY AND PRIVACY PROTECTION)

Ref.	Problem			Problem Solving			Objective	Restrictions
	PS	TA	DC	MOR	AI / ML	SPP		
[132]	X			Genetic algorithm	GNN		Optimize form teams	Worker Skill + Capacity constraint
[50]			X		GCN		Solve data sparsity problem	——
[133]	X				DL		Guarantee system robustness + Reduce transmission latency	——
[52]	X				Improved Q-learning method		Maximize long-term rewards	Area coverage ratio
[134]	X				Combined Multi-armed Bandit		Maximize task completion quality	Budget constraint
[135]	X	X			RL	privacy protection protocol algorithm	Achieve efficient task allocation	——
[53]		X	X		DDQN		Maximize platform profitability	Task and user related constraint
[136]		X		Clustering	DDQN		Improve task completion rate	Time and coverage constraint
[137]			X		DRL + GNN		Improve task completion rate	——
[138]		X			DDQN		Improve task coverage + Platform profit	Time constraint

7) Markov Model: Ding *et al.* in [46] investigated the probability of users being able to perform tasks through semi-Markov prediction and meta-path prediction. They assigned tasks based on these probabilities, which led to a more efficient task completion rate. In [128], authors established a Markov chain-based mobility model to predict the distribution of sensing nodes. They estimated the sensing capability of each sensing node, and proposed a sensing task allocation method to improve the quality of sensing data. Li *et al.* in [129] applied a semi-Markov model to predict the locations of workers and tasks. They proposed a prediction-based task allocation method to maximize the system utility and reduce worker costs.

8) Clustering: Based on worker preferences, authors in [48] proposed two cluster formation methods to determine cluster formation, route planning, and cluster groupings. They sorted the clusters and determined the best path for each cluster sequentially. Yang *et al.* in [130] reduced the maximum task span of all requesters in the opportunistic sensing scenario. They formulated a cluster-based task assignment problem, where clustering was performed based on the similarity of the requesters. Lu *et al.* in [131] focused on the issue of worker recruitment in mixed sensing scenarios. Opportunity workers were recruited offline and clustered into fixed areas online.

[AI and ML]

AI-related methods have also been applied in human-oriented sensing. Typical methods include DL [132], [50], [133], RL [52], [134], [135], DRL [53], [136], [138]. The summary and organization of these studies are listed in Table V.

1) DL: In [132], authors introduced two worker recruitment strategies (platform-based and leader-based strategies). They designed a low-complexity recruitment algorithm, where the search space was reduced by Graph Neural Networks (GNNs). Tong *et al.* in [50] proposed a multi-task and multi-attention Graph Convolutional Network (GCN) method for sensing data reconstruction and prediction. They developed a dynamic multi-task learning framework and utilized transforming attention blocks to mitigate error propagation. Zhou *et al.* in [133] introduced and validated a framework called RMCS (Robust Mobile Crowd Sensing), which integrates DL and edge computing. DL and edge computing were employed in the proposed framework for data validation and processing, respectively.

2) RL: Authors in [52] proposed an improved Q-learning method to address the exploding state value tables of traditional Q-learning. A two-stage online approach was proposed to select suitable participants to maximize long-term rewards. Based on the upper confidence bound, authors in [134] introduced a worker recruitment method under budget constraints. The problem was modeled as a combined multi-armed bandit problem to maximize task completion quality. Authors in [135] investigated a learning-based mechanism to ensure efficient task allocation. They explored a privacy protection protocol to safeguard location information, and an RL-based method to select participants.

3) DRL: Authors in [53] introduced a Double Deep Q-Network (DDQN)-based sensing task allocation framework. This framework integrated data collection, task allocation, and reward distribution processes. Similarly, a DDQN-based task allocation method was presented in [136], which assigns Points of Interest (POIs) to workers to detect and execute sensing tasks efficiently. Authors in [137] explored the challenge of uploading sensing data. They proposed a GNNs-based adaptive learning method, which improves data upload efficiency and demonstrates stable performance. Authors in [138] conducted task allocation and time-sensitive path planning issues in a DRL-based framework. The results showcased technical advancements in terms of task coverage and platform profit.

TABLE VI
SUMMERY OF INCENTIVE MECHANISM RESEARCH IN HUMAN-ORIENTED SENSING

Ref.	Problem			Problem Solving				Objective	Restrictions
	PS	TA	DC	MOR	AI / ML	IM	SPP		
[57]	X					Classical incentive		Maximize social welfare	Task quality requirement
[139]	X					Classical incentive		Establish market mechanism	Budget constraint
[140]	X					Classical incentive		Maximize service provider profit	Service quality constraint
[59]	X			Binary search + Heuristic method		Reverse auction		Maximize platform benefits	Cost/Budget constraint
[141]	X					Reverse auction		Maximize task completion rate	Cost constraint
[142]	X					Reverse auction		Minimize system cost	——
[143]	X				Multi-armed bandit	Three-stage Stackelberg game		Maximize the utility of requester and platform	Social-aware impact
[144]	X					Two-stage Stackelberg game		Maximize the benfits of parties	Budget and reputation constraint
[145]	X					Stackelberg game + Many-to-many bargaining		Improve platform revenue	Cost constraint
[63]	X		X			Contract theory	Trust	Maximize the utility of the platform and users	Ensure service quality
[64]			X			Contract mechanism		Maximize the utility of the platform	Service quality
[146]			X			Contract theory	Trust	Maximize the utility of the platform	Ensure service quality

[Incentive Mechanism]

Here, incentive mechanisms have been used to motivate participants to participate in the sensing process, including classical incentive method [57], [139], [140], auction theory [59], [141], [142], game theory [143], [144], [145], contract theory [63], [64], [146]. The summary and organization of these studies are listed in Table VI.

1) Classical Incentive Method: In [57], authors proposed a quality-driven incentive mechanism to maximize social welfare and ensure task quality. This mechanism motivated workers to participate in tasks by offering rewards of task performance. Liu *et al.* in [139] examined the market mechanism of crowdsensing under budget constraints. Considering the costs that users bore, they proposed a budget-based feasible approach, and devised an incentive mechanism to motivate participants. Similarly, authors in [140] proposed a financial reward-based incentive mechanism between users and service providers. They determined an equilibrium under dynamic market conditions to meet the user requirements.

2) Auction Theory: Zhou *et al.* in [59] investigated the bi-objective optimization problem in crowdsensing, where the objective is to maximize benefits under cost constraints. They designed a bi-objective reverse auction-based incentive mechanism through binary search and heuristic methods. Similarly, Wang *et al.* in [141] proposed a reverse auction-based incentive mechanism to motivate users to participate in sensing tasks. They obtained user selection and payment strategies by analyzing the interaction between the platform and users. Ji *et al.* in [142] proposed a reverse auction-based incentive mechanism to recruit suitable workers to minimize system costs. Here, workers with a high level of contribution to the system were selected through reverse auctions.

3) Game Theory: In [143], Xu *et al.* proposed a Stackelberg game-based incentive mechanism to attract workers who can perform tasks with high quality. To create a stable win-win situation, they solved the majority problem through a three-stage game model. Then, the utilities of requesters, platforms, and workers are maximized. Hu *et al.* in [144] designed a two-stage Stackelberg game between workers and service providers to maximize the benefits for both parties. They analyzed sensing data to determine the reputation of workers, and applied an inverse induction method to recruit reliable workers. Li *et al.* in [145] discussed the design of incentive mechanisms in competitive and non-competitive scenarios. The former was modeled as a Stackelberg game, and the latter was modeled as a many-to-many bargaining model.

4) Contract Theory: Dai *et al.* in [63] designed a trust-based contract mechanism in crowdsensing to maximize the utility of the platform and users. They designed an optimal contract based on user preferences to ensure individual rationality and incentive compatibility. Li *et al.* in [64] proposed two quality-based contract mechanisms for complete and incomplete information scenarios. In the former, the platform determined the expected contract and corresponding payment through the characteristics of users. In the latter, the platform designed a one-to-many contract to seek the optimal solution since user characteristics are private. In [146], authors proposed a contract theory-based sensing scheme to maximize the utility of the platform. They ensured sensing quality through a trust scheme, and established the optimal contractual relationship between the platform and users to achieve desired results.

[Security and Privacy Protection]

Several articles apply security techniques to protect privacy processes, including blockchain [65], [147], [148], trust management [67], [149], [150], encryption [69], [151], [152], anonymization [71], [153], [154], attack and defense [73], [155], [156], and others mixed methods [157], [158], [159]. The summary and organization of these studies are listed in Table VII.

1) Blockchain: Authors in [65] proposed a blockchain-based crowdsensing model that uses device reputation to enhance the security of the blockchain and sensing nodes. Meanwhile, they designed two smart contracts to control

TABLE VII
SUMMERY OF SECURITY AND PRIVACY PROTECTION RESEARCH IN HUMAN-ORIENTED SENSING

Ref.	Problem			Problem Solving				Objective	Restrictions
	PS	TA	DC	MOR	AI/ML	IM	SPP		
[65]	X						Smart contract + Reputation	Ensure the security of nodes	——
[147]	X					Three-stage Stackelberg game	Blockchain	Protect the privacy and sensing process	——
[148]	X			Heuristic-based approach			Smart contract	Protect the interaction process of MUs	——
[67]						Reverse auction	Trust evaluation	Ensure data trustfulness	Malicious nodes
[149]	X						Trust-based mechanism	Select hight trust nodes	Data quality
[150]	X						Reputation evaluation	Reduce task completion cost + Improve completion rate	Sensing cost
[69]	X			Greedy			Secret sharing scheme	Protect the security of the user recruitment process	——
[151]		X					Pallier cryptosystem	Minimize the movement distance of participants	
[152]	X						Symmetric homomorphic encryption	Increase the efficiency of worker assignment process	Spatial and temporal constraint
[71]	X						Differential privacy + Blockchain	Protect worker privacy	——
[153]		X		K-means clustering			Short group signature + 0-1 encoding	Secure matching	——
[154]	X						Anonymization protocol + Truth discovery	Reduce workers cost	——
[73]	X				DRL		Data poisoning attack	Evolve attack strategies	——
[155]		X	X				Attacks and defences against fog nodes	High-quality data collection	Spatial and temporal constraint
[156]	X				DRL		Multi-rounds of data poisoning	Improve system robustness	——
[157]	X						Anonymity policy + Homomorphic encryption + Blockchain	Protect user privacy	——
[158]	X						Blockchain + Reputation + Encryption	Protect worker selection process	——
[159]		X					proxy re-encryption + BBS+signature + Trust manaagement	Protect task allocation	——

the behavior of participants. Hu *et al.* in [147] considered to protect the privacy and sense process in crowdsensing via blockchains. In addition, an incentive mechanism based on fairness has been proposed to improve the effectiveness of participants. Moreover, Tao *et al.* in [148] proposed a blockchain-based decentralized sensing framework where the user interaction process was protected through smart contracts.

2) Trust Management: Wang *et al.* in [67] proposed a novel trust evaluation mechanism for crowdsourcing. Through edge computing technology, they assessed the trustworthiness of sensing nodes, and incentivized users to perform trust evaluation. The effectiveness of the proposed mechanism was demonstrated through detailed analysis. Based on the trust relationship obtained from the trust model, authors in [149] proposed a trust-based user recruitment mechanism to select highly trusted users and reduce security risks. In [150], authors proposed a reputation-based collaboration-sensing scheme. Reliability was assessed by evaluating the reputation of the nodes, and participants were grouped based on their reputation. They used the collaboration group to select the node with the highest reputation, while the non-collaboration group served as the baseline.

3) Encryption: Xiao *et al.* in [69] proposed a method to protect the security of the user recruitment process. They developed a user selection protocol based on a secret sharing scheme, and then employed a greedy approach to select optimal users. Zhao *et al.* in [151] investigated a bilateral privacy-preserving task assignment mechanism, which protects the privacy of both participants and task requesters. The mechanism utilized the Paillier cryptosystem to encrypt the task assignment information, and minimize the moving distance of participants. Zhang *et al.* in [152] proposed a worker selection scheme based on symmetric homomorphic encryption. This scheme not only protects the privacy of worker information but also improves the efficiency of workers performing tasks through pre-filtering.

4) Anonymization: Sun *et al.* in [71] proposed a two-stage privacy protection mechanism to protect the privacy of workers. They proposed a differential privacy-based approach to conceal worker location information, and uploaded the data to the blockchain and edge cloud for processing. Authors in [153] studied the task allocation method for privacy protection. They performed secure grouping by k-means clustering and matrix multiplication. Anonymous authentication based on short group signatures and 0-1 encoding is then guaranteed. Tang *et al.* in [154] proposed an anonymization protocol to protect worker privacy. To hide the relationship between workers and data, they propose a lightweight truth discovery protocol to reduce worker costs.

5) Attack and Defense: Authors in [73] raised the problem of poisoning attacks against partial observable data. They presented a DRL-based approach to data poisoning attacks which can assist malicious workers in hiding their hazards. Yao *et al.* in [155] proposed a spatiotemporal relevant task allocation scheme. They achieved high-quality data collection by optimal matching between tasks, fog nodes, and platforms. Meanwhile, attacks and defenses against fog nodes were considered. Zhang *et al.* in [156] investigated the multiple rounds of data poisoning in the truth discovery framework. They verified and optimized the vulnerability to improve the defense performance of the framework.

6) Hybrid Research: Several studies have considered security issues and applied security protection methods. Authors in [157] proposed a decentralized privacy protection model via blockchain. They established an elliptic curve algorithm-based anonymity policy and a homomorphic encryption algorithm to protect user privacy. Gao *et al.* in [158] investigated a blockchain and trust-based privacy protection scheme. They encrypted the reputation of workers through a deterministic encryption algorithm, and proposed a heap sorting-based worker selection scheme. Ni *et al.* in [159] proposed a privacy protection scheme to support sensing task allocation. They protected the privacy information of users through proxy re-encryption and BBS+signature. Then a trust management mechanism is proposed to determine the credibility of users without disclosing privacy. Meanwhile, a matrix multiplication of privacy-preserving location-based matching mechanism was used for task allocation.

[Others]

Typical works apply data structures to solve human-oriented sensing problems. Zhang *et al.* in [75] proposed an auction mechanism-based incentive tree model to motivate users to participate in sensing tasks. The tree structure was used to disseminate task information to potential users and increase participation. They designed a robust incentive tree mechanism to deal with malicious bidding behavior and Sybil attacks. Yin *et al.* in [76] considered the correlation between regions and performed tasks in different regions sequentially. The maximum correlation processing plan problem was formalized to generate trees with maximum correlation. They proposed an algorithm to generate a tree that connects all region nodes while ensuring maximum total correlation. Wang *et al.* in [160] investigated collaborative sensing in D2D networks. They created a weighted directed graph based on the mobility of users, and converted the problem into a search problem on the graph. A greedy-based optimization method was proposed to obtain the optimal solution. Furthermore, Wang *et al.* in [77] studied the user recruitment problem in human-oriented sensing. In the case of single-round recruitment, they transformed the user recruitment problem into a minimum-cut problem, and proposed a graph-based method. In the case of multi-round recruitment, they applied a combined multi-armed bandit model, and proposed a graph-based payment method to ensure the validity of problem.

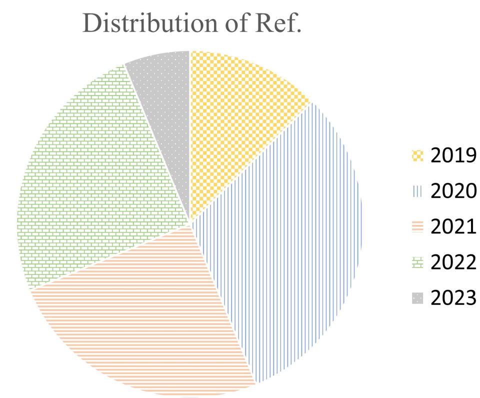

Fig. 12. The literature under human-oriented applications.

D. Typical Applications for Human-oriented Sensing

The methods used in human-oriented sensing offer solutions for various applications in smart cities, such as indoor management, environmental monitoring, and social management. This subsection analyzes the challenges and technologies involved in each practical application. Table VIII summarises the relevant applied research for human-oriented sensing. Meanwhile, the literature years of human-oriented sensing applications are shown in Fig. 12. In particular, in recent years, crowdsensing has shown development prospects in the field of smart agriculture. In the past three years, it has also shown advantages in virus transmission management.

1) Indoor Management: Generally, indoor positioning based on radio frequency fingerprints (such as WiFi and cellular signals) requires prior knowledge and user-specific information. Contrarily, Liu *et al.* in [28] proposed an updated radio map scheme that addressed positioning accuracy challenges. They assessed the integrity of fingerprints, and used adaptive estimation methods to determine the update status of access points.

Therefore, hybrid indoor mobile positioning schemes have been proposed in recent years. Accurate locations are obtained by combining Pedestrian Dead Reckoning (PDR) with WiFi fingerprint technology. Li *et al.* in [161] proposed a seamless indoor-outdoor positioning system based on crowdsensing called SoiCP. The system utilized PDR to automatically construct a radio map without prior knowledge of a floor plan. Then, a three-step trajectory matching algorithm is presented to construct the user's walking path. Finally, enhanced particle filters and other sensors are employed to achieve high-precision indoor positioning. Wu *et al.* studied crowdsensing-based indoor positioning systems in [162]. The original trajectory is first generated using PDR and then corrected to an almost realistic trajectory by optimization. Based on this, DL-trained inertial data and WiFi fingerprint samples are combined with a Kalman filter, which can eventually provide accurate localization.

In addition, it is possible to construct an image-based lightweight indoor positioning system. Tang *et al.* in [163] proposed an edge-assisted indoor image localization method called CrowdLoc. Here, multi-view localization is provided on

TABLE VIII
SUMMARY OF APPLICATION FOR HUMAN-ORIENTED SENSING

Applications		Ref.	Solved problems	Approach	Objective
Indoor Management	WiFi or cellular signals	[28]	localization accuracy + Fingerprints updated determination + New fingerprints capture	Fingerprint integrity assessment algorithm + Periodic adaptive estimate algorithm	Update the radio map efficiently
	Hybrid indoor mobile positioning	[161]	seamless indoor-outdoor positioning system	PDR + Three-step trajectory matching algorithm	Achieve high-precision indoor positioning
		[162]	Construct the inertial database + Wi-Fi radio map	PDR + DL +Optimization-based algorithm + Smoothing-based algorithm	Provide accurate localization
	Image-based lightweight indoor positioning	[163]	Unlabeled updated data + Crowdsourcing map update	Multi-view localization system + Map defect sensing algorithm + Cache classification algorithm	Edge-assisted indoor image localization
		[164]	Fuse multiple information sources related to location information + Achieve a highly accurate estimation position	Segmented structure adaptive calibration algorithm +Image-based subregion matching algorithm + Dynamic temporal warping algorithm	Indoor localization system with heterogeneous information fusion
Environment Monitoring	Urban pollution	[29]	Address location privacy	Trusted execution environment + Spatiotemporal compressed sensing method	Obtain the environment information
		[165]	Combining monitoring data with data from mobile phone-embedded sensors and time/space proximity	ML classification approach + Context awareness algorithm	Improve the reliability of MCS collected data
	Noise monitoring	[166]	Measure noise using mobile crowdsensing, store and analyze collected data	Develop mobile application to collect data + Big data infrastructure for storing data and real-time big data analysis + Web application for decision support	Development of a MCS system for noise pollution monitoring
		[167]	Collect data on urban environmental noise to study the relationship between sound and living things	Using MD to collect data + Sensing protocol according data	Monitor noise level
Social Management	Disaster management	[168]	Real-time information monitoring + Quickly and accurately determine the location of the disaster area + Quickly receive specific information on the impact of the disaster	Clustering + Message queue telemetry transport + Fuzzy logic-based decision support system	Design and implement disaster framework
		[169]	Show navigable paths to disaster victims and possible hazardous locations.	Blockchain + Smart contract + GPS location sequence	Create traversal maps
	Smart agriculture	[170]	Analyze the critical factors of combining MCS with agriculture.	Agriculture application scenario	Data collection methods in agriculture
		[171]	Analyze plant images + identify health issues using AI engine	Greedy + AI	Minimize smartphone number + Improve geographic coverage
	Virus transmission management	[30]	Early detection and isolation of potentially susceptible populations + Effectively control the epidemic of its disease	Spatio-temporal infected rate measure + Pruning strategy	Correctly address the infected rate on trajectories
		[172]	Predicting the risk of community transmission	K-means + Hidden markov models + Expectation maximisation	MCS-driven community risk modelling solutions
		[173]	Provide intelligent isolation strategy through MCS	Develop crowdsensing-based program + Epidemiological surveillance	Avoid spreading the virus

the client side, and low-confidence offloads are made to the edge server for accurate computation via crowdsourced maps. The cache of the crowdsourced map is then automatically updated on the edge side using a map defect-sensing approach. Finally, a cache elimination strategy is proposed with the aim of improving cache utilization. Li *et al.* in [164] studied an indoor positioning system using crowdsensing called Wimage. Location-related information sources can be fused by utilizing heterogeneous information, such as WiFi, images, etc. Then, the sub-region matching method of the image is used for positioning, and the matching trajectory is obtained through the weighted K-nearest neighbour method. The results show that Wimage can achieve high accuracy in large-scale indoor scenes.

2) Environment Monitoring: Crowdsensing is widely used in environmental monitoring, such as air quality and noise monitoring.

Urban Pollution: Bian *et al.* [29] proposed a new community sensing model for spatiotemporal environmental monitoring. This model collected environmental information in each sub-region, and each participant was choreographed for its trusted execution environment. Specifically, by dispersing sensing data for each sub-region, they proposed a gradient descent-based spatiotemporal compressed sensing method to optimize the learning data. In [165], authors proposed a machine-learning classification method to monitor urban pollution data. They used context awareness to improve confidence in data collection, and proposed ML methods for inferring unlabelled data from labeled data.

Noise Monitoring: In [166], authors explored a crowdsensing platform for monitoring and analyzing noise pollution in smart cities. The platform includes mobile applications, infrastructure for storing and analyzing real-time data, and applications for decision-making. After the data is preprocessed and sent to the cloud, they proposed a method to prioritize selecting uncovered locations to ensure continuous monitoring. In [167], authors tried to collect environmental noise through crowdsensing. They determined the relationship between noise

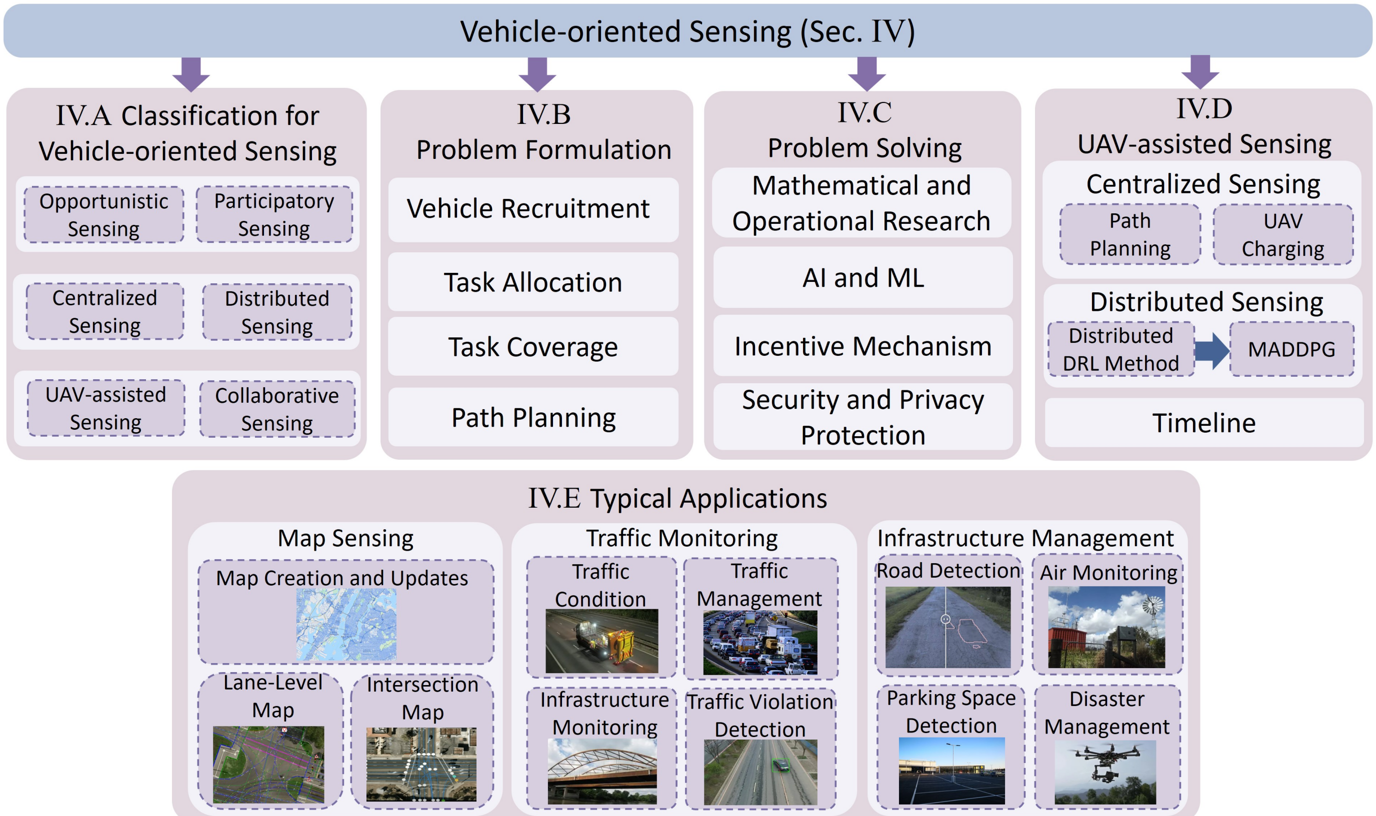

Fig. 13. The structure of section IV.

and citizens by analyzing contextualized urban noise data.

3) Social Management: Crowdsensing plays a significant role in social management, serving all aspects of society. Examples include disaster management, agricultural monitoring, virus transmission management, etc.

Disaster Management: Crowdsensing is a valuable means of post-disaster management. In [168], authors proposed a framework for post-disaster management based on crowdsensing. Specifically, they analyzed building damage using user-density data (IoT devices connected via cellular networks) and used a fuzzy logic decision mechanism to manage resources. Besides, as disasters damage infrastructure, GPS track information must be collected through IoT devices to collate available paths to the disaster site. For this, authors in [169] proposed a decentralized system for information management in post-disaster scenarios. To ensure accuracy, they uploaded the information to the blockchain after being processed through a smart contract.

Smart Agriculture: Crowdsensing also finds applications in agriculture. Sun *et al.* in [170] studied data collection in intelligent agriculture. They proposed a framework called AMCS, which offers significant flexibility, data collection efficiency, and cost advantages. The effectiveness of this framework was analyzed through a specific embodiment of solar insect-killing lamp maintenance. In [171], authors introduced a program to detect early plant diseases, which is employed on mobile devices. They investigated the deployment strategy and the incentive mechanism for users to reduce the required device number.

Virus Transmission Management: As viruses are highly transmissible and can cause social harm, countermeasures become essential. Crowdsensing can analyze the trajectory or other characteristic information of mobile users, thereby enabling protective measures to prevent the spread of the virus. He *et al.* in [30] proposed a crowdsensing-based method for determining the spatiotemporal infection rate. They obtained the collection of susceptible populations by analyzing the trajectories of populations at risk of infection. The spatial-first index method was introduced to analyze multiple trajectories in parallel to avoid redundancy.

Recently, the popularity of COVID-19 has led to the broader use of crowdsensing in virus transmission monitoring. In [172], authors studied a crowdsensing-based community risk modeling approach to monitor the prevalence of COVID-19. Here, communities were delineated based on the spatiotemporal aggregation characteristics of participants. The platform analyzed the mobile characteristics of participants and utilized ML methods to predict the transmission risk of each community. Besides, for the evolution of COVID-19 in Spain, authors in [173] examined crowdsensing-based response programs to prevent the spread of infection. It is possible to mitigate the impact of imposing restrictive measures to prevent viral propagation using crowdsensing-based programs. Epidemiological surveillance can also bring new suggestions for controlling the spread of the virus.

IV. Vehicle-oriented Sensing

This section first introduces the classification of vehicle-oriented sensing from different perspectives. Then, we also discuss the problem formulation of vehicle-oriented sensing and summarize the relevant literature. Regarding the four major technical classifications, we classify and discuss relevant research. Finally, we introduce typical applications for vehicle-oriented sensing. Fig. 13 shows the structure of Section IV.

A. Classification for Vehicle-oriented Sensing

In vehicle-oriented sensing, various classifications are employed based on different perspectives. For instance, classification in terms of different ways of participating in the sensing task, in terms of whether it is centralized or distributed, and in terms of sensing entities.

1) Opportunistic Sensing and Participatory Sensing: Depending on how the vehicle is involved in the sensing task, it can be divided into opportunistic and participatory vehicles. On the one hand, opportunistic vehicles execute tasks during their daily operations without need to change their routes. On the other hand, participatory vehicles are willing to alter their routes and proceed to designated locations for conducting sensing tasks. Correspondingly, sensing involving opportunistic vehicles is called opportunistic sensing, while sensing involving participatory vehicles is called participatory sensing. Fig. 14 shows two sensing methods.

Opportunistic Sensing: As stated above, in opportunistic sensing, the sensing entities are opportunistic vehicles. Opportunistic vehicles do not change their original trajectory to complete sensing tasks, but only complete tasks on their trajectory. Here, public vehicles such as buses can be considered as participatory vehicles in urban scenarios. Normally, such type of public vehicles have fixed routes, thus their routes cannot be altered. Therefore, they are only able to perform sensing tasks that exist along their routes, and receive corresponding task completion rewards. In opportunistic sensing scenarios, taxis or private cars also follow their original route and complete corresponding sensing tasks. This was the initially considered sensing scenario, where vehicles travel in an orderly manner. However, the fixed route of opportunistic vehicles also has drawbacks, which may lead to low task coverage. This is because sensing tasks may not be located along the vehicle's trajectory, so there is no opportunity to be completed.

Participatory Sensing: The emergence of participatory sensing overcomes the shortcoming of opportunistic sensing. In participatory sensing, the sensing entities are participatory vehicles. Participatory vehicles can be taxis that do not carry passengers or private cars with no destination intention. These vehicles do not fix their travel trajectory and are able to actively change their trajectory to complete the task based on the task's location. Compared to opportunistic vehicles, in addition to receiving rewards for completing tasks, there are also corresponding detour rewards for those been active sensing entities. Here, the detour reward is a floating reward related to the detour distance. However, participatory vehicles may diversions long distances to complete tasks for higher rewards, and this inevitably increases the overhead of the platform.

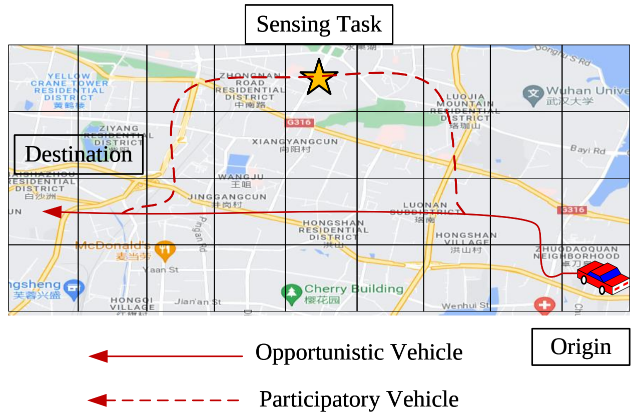

Fig. 14. The opportunistic sensing and participatory sensing.

Hybrid Sensing: Hybrid sensing, on the other hand, combines opportunistic sensing and participatory sensing, with advantages for improved task coverage and effective control of platform costs. Opportunistic sensing is typically performed by opportunistic vehicles, which follow a fixed trajectory to complete the sensing task on the route. Then, for the remaining uncompleted sensing tasks, the participatory vehicles could change their trajectory according to the task location and complete the sensing task. In this way, it can not only make up for the situation where opportunistic vehicles cannot complete tasks beyond the trajectory, but also effectively complete remaining tasks through participating vehicles and reduce the cost of the platform.

2) Centralized Sensing and Distributed Sensing: Centralized sensing is platform-centric sensing in which the platform makes global decisions and optimizes overall utility. On the contrary, distributed sensing is participants (vehicles)-centric sensing. Here, each participant can make corresponding decisions based on their situation and optimize their utility.

Centralized Sensing: From a platform perspective, Centralized sensing considers how to select vehicles to participate in tasks, how to assign tasks to vehicles etc. In addition, vehicle information and sensing data are processed uniformly through the platform. Centralized sensing has been the focus in previous years with extensive studies. In recent years, with the continuous increase in vehicle sensing capabilities, the platform may not promptly process large amounts of sensing data, resulting in additional delays. Moreover, centralized sensing faces increasing security issues such as leakage of sensing content. This has forced researchers to seek new solutions.

Distributed Sensing: From the perspective of participants, vehicles participating in the sensing process are willing to maximize its interests. This prmotes each vehicle the autonomy to make its own choices, allowing to observe its surroundings and make corresponding actions. In particular, the recent rise of multi-agent systems can be applied to distributed sensing scenarios. Similarly, decentralized systems such as blockchain can also be used, to protect system security in distributed sensing.

3) UAV-assisted Sensing and Collaborative Sensing: Recently, with the development of autonomous driving, UAVs have also been applied to the field of crowdsensing. The assistance of UAVs extends the sensing range to ordinarily inaccessible places, such as disaster scenes or potentially dangerous places. In addition, the emergence of UAVs has brought crowdsensing into a new dimension. The UAV enables sensing not only to be limited to 2D scenes but also to extend to 3D scenes. Thanks to their rapid deployment and controlled mobility, UAVs can be tailored to the current state of sensing to compensate for the sensing deficiencies of ground vehicles.

UAV-assisted Sensing: Typically, UAVs can be used as aerial sensing devices for urban sensing. Different from vehicle sensing, the UAV-assisted sensing is not limited by road traffic conditions that substantially impacts the sensing quality through vehicles. In summary, the UAV-assisted sensing offers three advantages: One is that UAVs can perform 3D sensing, which gears precise sensing for targeted locations at different heights. This shows significant advantages, especially in extreme environments such as forest fires, air pollution, etc. Secondly, UAVs have excellent mobility, can move flexibly and avoid obstacles. Thirdly, UAVs can be integrated with specialist high-precision sensors. For specific areas (e.g. solar panel inspection, crop monitoring), they can achieve a excellent sensing range and sensing capability than MDs. Thirdly, UAVs can be targeted with specialist high-precision sensors, enabling a more comprehensive range of sensing and more powerful sensing capabilities than MDs for specific areas (e.g. solar panel inspection and crop monitoring). Unfortunately, an obvious disadvantage to UAV-assisted sensing is the limited battery power. Therefore, many researchers have investigated energy-efficient sensing in energy-constrained scenarios.

Collaborative Sensing: Collaborative sensing is known as air-ground collaborative sensing. Due to the limited energy of UAVs, the sensing of air-ground collaboration can be considered. The ground sensing is performed where ground vehicles can reach, while UAVs act as an auxiliary for air sensing where ground vehicles cannot reach. Through collaborative sensing, the advantages of ground vehicles and UAVs can be effectively combined to improve sensing efficiency and avoid the impact of their respective disadvantages. Fig. 15 shows the UAV-assisted collaborative sensing scenario.

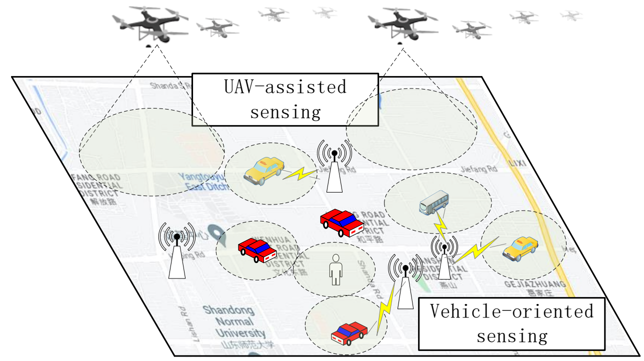

Fig. 15. The UAV-assisted collaborative sensing scenario.

B. Problem Formulation for Vehicle-oriented Sensing

Similar to human-oriented sensing, vehicle-oriented sensing also needs to address the issue of vehicle selection and task allocation. Table IX categorizes related problems and solutions for vehicle-oriented sensing.

1) Vehicle Recruitment: In the process of vehicle-oriented sensing, it is essential to select/recruit vehicles to participate in sensing tasks. As vehicles are considerably more mobile, this opens up more possibilities for sensing. Therefore, the vehicle's movement route is usually considered in the process of vehicle recruitment. Furthermore, recent studies also consider the state of traffic and the distribution of the road network, for the selection of vehicles.

Certain researchers have considered the effect of vehicle trajectories in the vehicle selection process. Hu *et al.* in [174] proposed a participant recruitment method with variable duration. In a limited budget scenario, vehicle uncertainty trajectories are considered to determine the selected vehicle and the length of service provided. Then, a two-step recruitment algorithm is designed to maximize the utilization of sensing resources. Authors in [175] jointly considered reputation and vehicle trajectories. A vehicle recruitment plan is designed through reputation assessment and service pricing, to maximize coverage with minimal cost. Then, a greedy-based heuristic algorithm for real-time vehicle selection is proposed.

Certain researchers have considered the impact of urban road networks or traffic flows. Yu *et al.* in [176] considered improving perceived utility by optimizing vehicle selection and proposed a spatiotemporal node optimization model based on road networks. In addition to considering road network coverage, the impact of the spatiotemporal characteristics of traffic flow is also considered. The concept of effective coverage and dynamic accessibility is introduced to maximize the perceived utility of urban traffic. In [177], authors considered QoS improvement of the system by optimizing service nodes (vehicles). Here, a QoS utility function is designed and calculated based on coverage and data scores. Then, a service node optimization model is designed, to select vehicles that can maximize the QoS utility of sensing task. In addition, the mobility of vehicles and the topology of the urban road network are also considered in the vehicle selection process. Yu *et al.* in [178] considered the importance of road networks and then conducted efficient vehicle recruitment. The objective is to achieve more excellent sensing coverage by recruiting limited vehicles. The performance of the proposed method is analyzed, by varying the congestion level of the road network.

2) Task Allocation: Due to the focus on vehicle mobility and trajectory during vehicle-oriented sensing, the task allocation is not as fine-grained as in the case of human-oriented sensing studies. However, this does not impact the way to formulate the task allocation, and the task types analyzed in human-oriented sensing also apply to vehicle-oriented sensing. Of course, adcanved study in task allocation problem for vehicle-oriented sensing still needs further research.

Several studies have focused on the traditional task alloca-

TABLE IX
PROBLEM FORMULATION FOR VEHICLE-ORIENTED SENSING

Pro.	Type	Ref.	Objective	Approach	Restrictions
Vehicle Recruitment	Vehicle trajectory effect	[174]	Maximize sensing resource utilization	Two-step duration-variable participant recruitment algorithm	Budget constraint
		[175]	Maximize coverage with minimal cost	Greedy-based heuristic algorithm	Reputation + Vehicle trajectory
	Urban road networks or traffic flows impact	[176]	Improve sensing utility	Node selection method	Spatiotemporal characteristics of road network
		[177]	Improve system QoS	Service node selection method	Vehicle mobility + Urban road network topology
		[178]	Maximize senisng coverage	Efficient vehicle recruiting scheme	Road network congestion
Task Allocation	traditional	[179]	Optimize task execution cost + execution time	Heuristic algorithm	Location constraint
		[180]	Improve sensing quality	Heuristic algorithm	Sensor type constraint
	Vehicle mobility	[181]	Minimize task execution cost	Greedy + Logistic regression	Deterministic + Non-deterministic trajectory
		[182]	Maximize the connection time between workers and edge nodes	RL	Budget constraint
Task Coverage	Vehicle trajectory	[183]	Improve sensing coverage	Analyze the trajectory of taxis	Taxi trajectory
		[184]	Improve task coverage	Improved A^* algorithm + Probabilistic manner	Total length of the path
		[185]	Achieve road coverage + Reduce cost	Path selection method + Distributed stochastic approach	Budget constraint
	Hybrid sensing	[186]	Improve task coverage	Optimal route search + Integrated route selection + Final route determination	Vehicle trajectory
		[187]	Maximize task coverage	Kuhn-Munkres-based task assignment + Greedy	Heterogeneous users limit
Path Planning	Directly select	[188]	Route planning framework	Build sensing databases of road quality and individual driver skills in different driving environments	——
		[189]	Maximize the overall sensing benefit	Heuristic algorithm	Road importance
	Multiple candidate paths	[190]	Finde the most suitable path	Path selection algorithm	Cost constraint
		[191]	Increase user total profit	Game theory + Distributed path selection method	Budget constraint

tion problem in vehicle-oriented sensing. In [179], Chen *et al.* investigated a fog-based vehicle-oriented sensing scheme in which vehicles can act as fog nodes. The scheme combines task allocation and participant selection, to optimize task execution cost and execution time. Then, a heuristic algorithm based on stochastic chemical reaction optimization is proposed to solve the above problems. In [180], authors studied the task allocation problem in vehicle-oriented sensing, with the goal to improve the sensing quality of multidimensional vehicle city sensing. By modularizing the problem, a heuristic algorithm using the nature of submodules is designed, to ensure good completion of sensing task allocation under low complexity conditions.

Several studies have focused on the problem of task allocation considering vehicle mobility. Tu *et al.* proposed a vehicle-oriented task allocation problem in [181], with the goal of minimizing task execution costs. According to the dynamics of vehicle trajectory, it is divided into deterministic and non-deterministic trajectory problems. For the deterministic trajectory problem, a greedy-based approach is proposed. For the non-deterministic trajectory problem, the probability of each trajectory is first determined using logistic regression. Then, the probability of vehicle performing the task is determined by a semi-Markov method. Finally, the same greedy-based solution is given. By utilizing collaboration between edge nodes [182], repetitive task assignments caused by vehicle mobility can be avoided, such that the contact time between vehicles and edge nodes can be increased.

3) Task Coverage: The task coverage is a critical issue in vehicle-oriented sensing. Appropriate strategies are required to ensure the task execution rate. Both the higher utility of vehicle or platform and the higher satisfaction of task initiator, can be achieved by higher the task coverage. Therefore, improving task coverage will be a three-win situation. As mentioned in the previous section, hybrid sensing and air-ground collaborative sensing aim to improve task coverage. Hence, numerous researchers have investigated the problem of how to improve task coverage in vehicle-oriented sensing.

Several studies have considered improving task coverage by analyzing the trajectory of vehicles. Authors in [183] studied the possibility of using taxis as sensing vehicles. By analyzing the trajectory of 100 taxis in Porto, it is found that they can effectively sense the complex urban road network and achieve high perceived coverage. Due to the uneven distribution of vehicles in the road network, authors in [184] proposed a vehicle-oriented sensing coverage method based on the improved A^* algorithm. Under the constraint of the total length of the path, a suitable path is selected in a probabilistic manner and exhibits good performance in terms of task coverage. Authors in [185] proposed a budget-constrained sensing routing method named ROUTR, with the goal of achieving uniform road network coverage and reducing costs. Monetary rewards are paid to the vehicle to incentivize its path selection, making its policy more consistent with the target distribution. Here, the path selection method is optimized based on A^*, and the random factor probability is used to select the path to ensure that the cost is within the budget limit. The potential path area is then applied to determine the set of eligible paths to solve the problem through a distributed stochastic approach.

Several studies have investigated the problem of task coverage in hybrid sensing scenarios. Zhu *et al.* in [186] proposed a crowd-assisted vehicle hybrid sensing scheme. The collaboration between dedicated sensing vehicles and MUs is used to improve task coverage. The route planning of dedicated sensing vehicles is carried out through three aspects: optimal route search, integrated route selection, and final route determination. The strategies of MUs are based on a novel selection strategy. Liu *et al.* in [187] studied the duration sensing problem of heterogeneous users, where users are divided into vehicle users and pedestrian users. The objective is to maximize task coverage through task assignments. From the perspective of pedestrian users, a Kuhn-Munkres-based task assignment method is proposed. From the perspective of vehicle users, a greedy task allocation method is proposed.

4) Path Planning: In participatory sensing, vehicles can choose a route that meets their interests based on the current environment. Meanwhile, the platform can also personalize and recommend candidate trajectories for vehicles to choose from. In light of this, planning routes for vehicles to improve their satisfaction or sensing tasks are of importance.

Several articles have investigated the optimal path selection for the vehicle directly, by analyzing the environment and state. Authors studied a path planning scheme in [188]. A sensing database of road conditions and drivers' unique skills in different driving environments is created based on vehicle sensors. Then, based on this information, drivers are provided with paths that match their preferences. Lai *et al.* in [189] studied a more realistic vehicle sensing framework. The framework includes vehicle recruitment, candidate path analysis, and path selection. Here, vehicle preferences and interests are analyzed based on historical vehicle trajectory information, which is used to select the most promising vehicles. Then, the maximum weighted path detection problem is proposed using the sensing strategy of minimum disruption. The path with the least trip disruption and the greatest benefit is selected for the vehicle.

Several articles have investigated the selection of the suitable route from multiple candidate paths. Authors in [190] selected a suitable path for the vehicle, considering both direct and indirect factors that affect travel time. First, all eligible paths for the vehicle are listed. Then, travel costs are estimated based on distance costs and other indirect factors, where the path with the lowest cost is selected. The travel cost here includes not only the distance cost but also considers road conditions, environmental factors, traffic flow, etc. Wang *et al.* in [191] studied the distributed path navigation method. The system first recommends multiple candidate routes to the vehicle, each covering different sensing tasks. Then, vehicles choose the route that suits their own interests. Due to the shared task rewards among all vehicles, the selection strategies of each vehicle inevitably create contention. Thus, authors modelled this problem as a multi-vehicle sensing game model to analyze the interaction among vehicles. Finally, they proposed a distributed path selection method.

C. Problem Solving and Strategies for Vehicle-oriented Sensing

In this subsection, we summarize the research on vehicle-oriented sensing, matching and presenting it according to four major technology categories. Here, AI and ML methods are more widely used in vehicle-oriented sensing, which will be described in detail below. Table X summarizes the relevant research on vehicle-oriented sensing.

[Mathematical and Operational Research]

As vehicle sensing systems face high dynamics and uncertainties, traditional mathematical methods are difficult for problem solving. This usually faces a highly complex computing state, consumes a large number of computing resources, and is difficult to obtain an optimal solution. Therefore, only a few studies have applied mathematical and operational methods in vehicle sensing-oriented scenarios. Specifically, these articles conduct research based on greedy algorithm [35], dynamic programming [39], particle swarm optimization [41], heuristic methods [45], [192], Markov models [47], and clustering methods [49].

1) Greedy Algorithm: In vehicle-oriented sensing, several studies have applied greedy ideas to solve problems [39], [181], [187]. However, the greedy algorithm is often used as a benchmark scheme in simulation experiments. Wang *et al.* in [35] proposed a vehicle recruitment method for vehicle-oriented sensing. Vehicle trajectories are predicted by deterministic and probabilistic models with the goal of reducing recruitment costs. A heuristic based on LP relaxation is proposed to solve the problem in a deterministic trajectory model. A greedy approach is proposed to solve the problem in a deterministic trajectory model, achieving good performance while guaranteeing the approximation ratio.

2) Dynamic Programming: Liu *et al.* in [39] proposed an edge-assisted collaborative data collection scheme. With the assistance of edge servers, sensing data is collected by both dedicated and non-dedicated vehicles to improve the spatiotemporal balance of data collection. Then, the offline and online scheduling methods are designed using dynamic programming and greedy ideas.

3) Particle swarm optimization: Liu *et al.* in [41] studied the issue of improving the efficiency of vehicle sensing networks. In order to increase the quality of vehicle service and network efficiency, a bi-objective optimization problem has been formulated with the goal of maximizing user satisfaction. Then the problem is decoupled, with the low-complexity methods of particle swarm optimization and convex optimization applied.

TABLE X
RESEARCH SUMMERY OF VEHICLE-ORIENTED SENSING (VR: VEHICLE RECRUITMENT, TC: TASK COVERAGE, PP: PATH PLAN)

Ref.	Problem				Problem Solving				Objective	Restrictions
	VR	TA	TC	PP	MOR	AI / ML	IM	SPP		
[35]	X				Greedy + Heuristic alogorithm				Reduce recruitment cost	Vehicle trajectory
[39]	X		X		DP + Greedy				Improve the spatiotemporal balance of data collection	Guarante spatial temporal coverage
[41]	X				PSO + Convex optimization				Maximize user satisfaction	Network redundancy + Budget
[45]	X		X		Heuristic method				Maximize sensing coverage	Budget constraint
[192]	X				Heuristic method				Reduce sensing cost + Collect more sensing data	Budget constraint
[47]				X	Markov-based mobility prediction				Improve sensing coverage	Budget constraint
[49]	X		X		Clustering + Online parameter adjustment method				Ensure the balance between sensing quality and communication overhead	Cost and data quality
[193]	X				Greedy-based online method	DL			Maximize sensing data volume	Budget constraint
[194]				X		PPO + DQN			Improve sensing coverage	User weight
[195]						Q-learning + Fuzzy logic			Reduce communication cost	Delay constraint
[196]		X				RL		Blockchain	Improve task utility	Budget constraint
[197]			X			DCN + LSTM + DRL			Improve data collection + Reduce vehicle energy + Ensure geographical fairness	——
[198]	X					PPO	Game theory		Optimal sensing strategy	Budget constraint
[51]		X				DDQN + GAT			Maximize total profit	Budget constraint
[199]				X		GCN + MARL			Improve sensing quality + Spatial-temporal sensing coverage	——
[54]				X		CNN + AC + LSTM			Reduce energy consumption	Energy constraint
[58]				X			Classical incentive		Make the sensing data distribution close to the target distribution	Budget constraint
[200]	X					ML	Monetary incentive		Reduce cost	Budget constraint
[60]				X			Reverse auction		Achieve broader task coverage	Spatiotemporal constraint
[201]	X						Reverse auction		Minimize social cost	Vehicle trajectory
[202]		X					Reverse auction		Increase requester utility	Budget constraint
[203]		X					Reverse auction	Blockchain	Maximize system welfare	Budget constraint
[204]	X						Reverse auction	Blockchain	Maximize social benefit	Budget constraint
[61]				X			Non-cooperative game		Improve sensing coverage	Budget constraint
[205]	X				Heuristic method		Bargaining theory		Maximize vehicle benefit	Spatiotemporal constraint
[206]	X				Clustering		Stackelberg game	Reputation management	Improve high-quality data	——
[207]		X		X	Hybrid gradient-based approach		Mean-field game theory		Improve energy efficiency	Resource constraint
[66]	X						reverse auction	Blockchain + Reputation	improve sensing quality + reduce cost	Budget constraint
[208]	X						Coalition game	Blockchain	Reduce vehicle cost	——
[68]								Blockchain + Reputation + TEE	Balancing efficiency and safety constraints	——
[209]	X							Blockchain + Reputation	Improve service quality	——
[210]	X				Matching theory		Monetary incentive	Blockchain + Reputation	Improve sensing data quality	Budget constraint
[70]								Secret-sharing technique + Key protocol	Guarantee the data privacy of vehicles	——
[211]								Homomorphic encryption + Zero-knowledge proof + Blockchain	Protect vehicle information	——
[212]	X							RSA encryption + Location authentication	Protect vehicle information	——
[72]								Blind signature	Preserve data credibility	——
[213]				X				Differential privacy	Protect vehicle information	——
[214]		X			Linear optimization			Differential privacy	Protect location privacy + Improve task quality	——
[74]						GAN		Predicte attack sample	Detect illegal sensing service request	——
[215]								Security loophole + Threat + Attack method	Assessing the hazards to road safety	——
[216]	X						Stackelberg game	Model perturbation defence + Differential privacy	Improve model reasoning efficiency	——
[217]	X						Reverse auction	Smart contract + Anonymous authentication	Improve data quality	Budget constraint
[218]	X	X						K-anonymity + Homomorphic encryption + Reputation	Selecte reliable vehicle + Reduce sensing costs	——
[219]		X				DQN		Blockchain + Attack	Improve system performance + protect data security	——

4) Other Heuristic Algorithm: Han *et al.* in [45] studied a vehicle recruitment method based on vehicle trajectory. Here, a heuristic method is proposed to simplify the vehicle recruitment process. Then, considering the mobility of vehicles, an online method based on dynamic thresholds is proposed. Finally, the effectiveness of proposed method is analyzed in both online and offline scenarios. Authors in [192] studied the vehicle recruitment problem in vehicle-oriented sensing to reduce the cost of sensing and collect more sensing data.

5) Markov Model: Chen *et al.* in [47] proposed a prediction-based vehicle sensing system, with the goal of improving sensing coverage under budget constraints. First, a Markov-based mobility prediction model is proposed, to improve the sensing coverage by predicting the probability of future trajectories. Then based on the predicted results, a drive planning method is proposed to determine the specific driven vehicles and corresponding trajectories.

6) Clustering: Liu *et al.* in [49] studied edge-assisted sensing data collection methods, and considered the collection cost and data quality. Here, an adaptive clustering method is proposed to cluster vehicles and support stable real-time data upload. Upon that, an online sensing parameter adjustment method is proposed to adjust the vehicle's strategy according to the actual traffic state, meanwhile to ensure the balance between sensing quality and communication overhead.

[AI and ML]

As the scale and complexity of the problems to be solved for vehicle-oriented sensing grow, traditional optimization methods are becoming overwhelmed. Here, ML and AI methods can easily cope, especially DRL methods. The optimal decision is obtained through the interaction between the agent and the environment, while the acquisition of actions is accelerated through neural network training.

1) DL: Nowadays, DL methods alone are often used to predict vehicle positions or paths. Most of the research combines DL methods with RL to obtain better results. Zhu *et al.* in [193] studied DL-based vehicle sensing methods. Here, a DL-based offline method is proposed to predict the mobility of vehicles, then a greedy-based online method is proposed to recruit vehicles. The goal is to maximize the amount of collected sensing data within a limited budget.

2) RL: Tang *et al.* in [194] proposed a multi-agent-based RL method to achieve better sensing coverage by scheduling vehicle paths. Then, the vehicles' own defined weights are added to the RL environment. Finally, two RL methods, Proximal Policy Optimization (PPO) and deep Q-networks, are applied to solve the proposed problem. Zheng *et al.* in [195] studied edge-assisted vehicle crowdsensing with the goal of reducing communication costs within a delay tolerance range. Then Q-learning-based offloading decision is proposed to achieve the above goal. The fuzzy logic method is introduced to adjust the hyperparameters to improve the offloading efficiency. Li *et al.* in [196] studied the problem of concurrent task assignment in vehicle crowdsensing and established a blockchain-based decentralized scheme. Here, the RL-based task assignment method is proposed, to meet the needs of safety emergencies and improve the utility of tasks.

3) DRL: Liu *et al.* in [197] proposed a distributed multi-tasking approach based on DRL named DRL-MTVCS. The goal is to improve data collection while reducing vehicle energy consumption and ensuring geographical fairness. The task spatiotemporal information is extracted using Deep Convolutional Networks (DCN) and long short-term memory. Adaptive normalization and pixel control are then added to enhance the model's effectiveness. Zhao *et al.* in [198] studied non-cooperative vehicle sensing methods. Sensing tasks are dynamically priced, and vehicles are incentivized to participate in sensing tasks through the vehicle social network. To obtain the long-term optimal sensing decision of vehicles, a DRL-based social sensing incentive mechanism named DRL-SIM is proposed. Xu *et al.* in [51] combined GAT and DRL to solve the problem of sensing task allocation. The method can flexibly and adaptively adjust actions according to the environment. Here, GAT is integrated into the training process of DRL, and the DDQN method is applied to continuously learn during the training phase to ensure favourable actions in the decision-making phase.

Due to the intelligence of vehicles, recent studies consider the scenario of distributed sensing, where each vehicle can act as an agent to make decisions. Ding *et al.* in [199] proposed a multi-agent RL method based on graph convolution cooperation named GCC-MARL. This method can assist taxis in distributed decision-making and collaborative optimization of global objectives. Each vehicle acts as an agent, and a credit allocation method is introduced to facilitate cooperation among vehicles. Finally, a graph convolutional network is combined to collect spatial characteristics from the complex road network to guide the vehicle's actions. Liu *et al.* in [54] proposed a distributed multi-agent DRL approach for energy-efficient and distributed unmanned vehicle scheduling. The feature extracted by CNN is used as the input of the AC network, which generates real-time actions and guides the trajectory of unmanned vehicles. Better exploration is achieved using long-short-term memory networks and distributed-prioritized experience replay. Through this method, the energy consumption of unmanned vehicles to perform tasks can be reduced.

[Incentive Mechanism]

In vehicle-oriented sensing, it is also necessary to motivate the vehicle to participate in sensing tasks. In particular, the vehicle can be motivated to change its original trajectory to complete more tasks. At present, there have been many studies applying classical incentives [58], [200], auction theory [60], [201], [202], [203], [204] and game theory [61], [205], [206], [207] to motivate vehicles.

1) Classical Incentive: Xu *et al.* in [58] proposed an incentive mechanism for vehicle crowdsensing, with the goal of incentivizing vehicles to make the sensing data distribution close to the target distribution under budget constraints. Vehicles are incentivized with fixed monetary rewards and floating rewards tied to destination tasks. The problem is transformed into a nonlinear multiple-choice knapsack problem. The difference between the target and actual distributions is used as the objective function. Finally, an optimization method named iLOCuS is proposed to solve this problem. Wang *et al.* in [200] proposed a sensing-based spectrum-sharing scheme for 5G networks. Here, a crowdsourced spectrum database is built through vehicles, with the goal of reducing costs and applying ML classifiers to select the points to interpolate vehicles. Then, an online and offline incentive mechanism based on monetary rewards is proposed to attract vehicles to participate in the sensing tasks.

2) Auction Theory: Fan *et al.* in [60] proposed a method called Hector for joint trajectory scheduling and incentive mechanisms, for vehicle sensing networks. Here, vehicle trajectories are mapped into sets with spatiotemporal constraints to reduce the complexity of problem solution. Then, a reverse auction incentive mechanism is designed to incentivize vehicles to detour to achieve broader task coverage. The proposed Hector can perform real-time vehicle trajectory scheduling and vehicle excitation. Gao *et al.* in [201] studied the incentive mechanism based on vehicle non-determinism. Here, vehicles are incentivized to participate in sensing tasks by establishing a reverse auction model between the platform and vehicles. In addition, the sensing data quality of vehicles is considered, with the winner selection method and payment determination method proposed accordingly. Chen *et al.* in [202] proposed a timeliness-based incentive mechanism. Here, a reverse auction model is established between the service requester and vehicles. Then, considering the uncertainty of vehicle travel time, a time distribution estimation method based on a discrete-time traffic model is proposed. Last, the auction problem is transformed into a non-monotonic submodule maximization problem, with the goal of increasing the utility of requesters subject to budget constraints.

Several studies design auction mechanisms in the blockchain scenario to ensure the security of the auction process. Wang *et al.* in [203] proposed a non-deterministic collaboration scheme based on blockchain, which is applied to the collaboration between vehicle teams in vehicle-oriented sensing systems. Here, a winner selection method based on the reverse auction mechanism is proposed to determine the task allocation strategy. Then, a credit-based team payment approach is proposed that can maximize system welfare. Finally, a blockchain-based framework is proposed to address trust and security issues. Zhao *et al.* in [204] proposed an air-space-ground integrated vehicle sensing network. Here, the blockchain is applied to solve the trust and safety issues between vehicles. Then, a reverse auction-based incentive mechanism is proposed, to motivate vehicles to complete the sensing task and maximize social benefits.

3) Game Theory: Various game methods are used to motivate vehicles to participate in sensing tasks. Such as the non-cooperative game, bargaining theory, the Stackelberg game, etc.

- The non-cooperative game can be used to model the interactions among vehicles. Authors in [61] studied the incentive mechanism in vehicle-oriented sensing, to stimulate vehicles to change their original trajectory and travel to remote areas. The problem is modelled as a non-cooperative game among vehicles, and the strategy is the new trajectory. A stable set of new trajectories is sought through the game, and the sensing coverage can be improved.
- The bargaining model is a dynamic game method with complete information. In [205], Liu *et al.* proposed an edge-assisted sensing vehicle recruitment approach. An incentive mechanism based on bargaining theory is first designed and used to facilitate collaboration between edge servers and vehicles. Then, a heuristic method is proposed to recruit vehicles, with the goal of maximizing the benefits of vehicles.
- The Stackelberg game model is also a dynamic game method with complete information. In [206], yin *et al.* devised an incentive mechanism called V-IMCS, applied to crowdsensing in vehicular ad hoc networks. Due to the possibility of vehicles providing malicious data, it is necessary to motivate vehicles to provide high-quality data. A Stackelberg game-based model is proposed to solve this problem. In addition, clustering methods and reputation management are applied to balance the competition between vehicles and process data according to priority.
- Kang *et al.* in [207] applied mean-field game theory, which is an approach that introduces mean-field theory to game theory. Authors studied the path planning and task selection issues in vehicle crowdsensing from the perspective of energy efficiency. The interactions among vehicles are modelled as a mean-field game problem. Then, a hybrid gradient-based approach is proposed which is independent of the number of vehicles in terms of complexity.

[Security and Privacy Protection]

In vehicle-oriented sensing, security and privacy protection issues have received more attention. In particular, researchers are accustomed to mixing multiple approaches to address security problems [217], [218], [219]. In this part, security protection methods for blockchain [66], [208], trust management [68], [209], [210], encryption [70], [211], [212], anonymization [72], [213], [214], and attack and defense [74], [215], [216] are introduced in detail.

1) Blockchain: Due to its decentralized nature, blockchain is often used to construct a secure distributed framework and serve as the basis for research on other security issues. Li *et al.* in [66] studied the incentive mechanism of blockchain-based vehicle sensing. A distributed platform is first established using RSUs as miners, and a blockchain is generated. The smart contract is used to automate the execution of the sensing process. The reputation of vehicles is then considered, and an incentive mechanism based on reverse auction is designed with the goal of improving sensing quality and reducing costs. Hui *et al.* in [208] studied a blockchain-based collaborative vehicle sensing method called BCC. A transaction architecture is designed using blockchain to ensure the security and privacy of the sensing environment. On this basis, a coalition game among vehicles is designed to encourage vehicle collaboration to complete sensing tasks. The optimal coalition is selected to reduce vehicle costs using the coalition formation method.

2) Trust Management: Recently, researchers have been keen to combine blockchain and trust models to ensure trust management in a secure scenario. Wang *et al.* in [68] studied blockchain-based trust management methods. Here, a blockchain-based trust evaluation model is designed to determine the trust value of each vehicle. Then, the trust value is protected to ensure credibility and transparency. A secure trust evaluation is provided through a trusted execution environment, and the blockchain is maintained based on trust proofs to improve scalability. Sun *et al.* in [209] proposed a sensing scheme based on blockchain and reputation called RC-chain. Here, a blockchain-based platform is created, by applying smart contracts to manage the transaction process. Then, a reputation model is designed and aggregated with the blockchain, to prevent malicious behaviour of vehicles. In addition, trust propagation and feedback similarity models are applied to analyze malicious service providers to improve service quality. Ma *et al.* in [210] proposed a blockchain-assisted vehicle crowdsourcing system to achieve secure vehicle reputation management in a distributed manner. Then, a vehicle selection method is proposed, which combines vehicle reputation with data quality to evaluate vehicle reliability. Finally, an effective incentive mechanism is proposed to promote high-reputation vehicles to participate in sensing tasks to improve sensing data quality.

3) Encryption: Authors in [70] proposed a truth discovery scheme for privacy protection, which is used for vehicle-oriented sensing. Here, secret-sharing techniques and key protocols are applied so vehicles can be taken offline anytime. A double mask is also applied to guarantee the randomness and irreducibility of the key, so as to guarantee the data privacy of the vehicle. Zhang *et al.* in [211] studied the distributed vehicle location privacy preservation problem. The platform's control over vehicle data is first eliminated through the blockchain. Then, homomorphic encryption and circle-based location verification are applied to protect the location information of tasks. In addition, the position of vehicle is replaced by the position of the grid, realizing the privacy protection of vehicle information. Finally, order preservation encryption and zero-knowledge proof are applied to prevent vehicles from forging location information for profit. Wang *et al.* in [212] studied a vehicle recruitment method based on location authentication. The method can realize location information verification and key transmission without keys sharing. During the vehicle recruitment process, there is no need to disclose private information to the platform. In addition, vehicle recruitment information is collected through trusted institutions, and RSA encryption is used to prevent information leakage.

4) Anonymization: Xu *et al.* in [72] studied a lightweight fog-aided vehicle-oriented sensing framework called TPSense. To preserve the credibility of the data, the proposed problem is modelled as a maximum likelihood estimation problem and solved using the expectation-maximization method. To protect the privacy information of vehicles, blind signature technology is introduced to anonymize vehicle identities to protect vehicle information.

Recent studies use differential privacy to confuse the information to be protected with its identity information to protect privacy. Authors proposed a privacy-preserving method for vehicle location in [213]. The vehicle paths are analyzed to evaluate the impact of proposed method. A shared location solution based on differential privacy is proposed, and the vehicle spatiotemporal data is converted into a graph, so as to improve the scheme's applicability. Qian *et al.* in [214] jointly considered location privacy preservation and perceived quality of service. Then, they proposed the task assignment problem in vehicular sensing networks. The location information of vehicles is protected by differential privacy, the actual location information is replaced with obfuscated location information and uploaded to the platform. Finally, in order to improve the quality of task completion and reduce the moving distance, it is decomposed into two optimization problems for solution.

5) Attack and Defense: Chen *et al.* in [74] proposed a Generative Adversarial Network-based (GAN) model for detecting illegal sensing service requests. A two-level cascaded classifier is proposed, combined with the discriminator of the GAN, to prevent fake adversarial tasks by predicting attack samples. Bian *et al.* in [215] discussed security threats for vehicle-oriented sensing. According to the related security loopholes, the threats are classified, and related attack methods are introduced. Then, the attack method is evaluated to judge its harm to road safety. Finally, solutions are discussed to achieve safe sensing scenarios. Wu *et al.* in [216] studied attacks and defences for collaborative reasoning in vehicular sensing networks. It is first verified that an attacker can reconstruct the data without knowledge of deep model. Then, a model perturbation defence method is proposed, defended by adding random Laplacian noise. Finally, an incentive mechanism is proposed to compensate for the loss of vehicle privacy and attract vehicles to participate in collaborative reasoning.

6) Hybrid Research: Several studies combine multiple methods and solve problems from multiple perspectives. Wang *et al.* studied a privacy-based incentive mechanism for vehicle crowdsensing in [217]. Smart contracts are utilized to protect the transaction process, and then a reverse auction method based on budget constraints is proposed. The vehicle privacy is ensured using anonymous authentication methods based on zero-knowledge proofs. Besides, the vehicle reputation and data quality are also used to measure vehicle rewards, and penalties are applied to malicious vehicles. Cheng *et al.* in [218] studied a sensing task allocation scheme for privacy protection. The scheme utilized Hadamard products and k-anonymity to protect location information, pseudonymity technology to protect identity information, homomorphic encryption to protect sensing data, and commitment technology to protect reputation value. The cost of vehicles is also reduced by reducing the number of interaction rounds. In addition, a reliability assessment method is proposed to prevent the vehicle's reputation value from being modified. Finally, a reputation value update method based on three factors is proposed to update the reputation value. Lin *et al.* in [219] proposed a vehicle crowdsourcing scheme based on DRL and blockchain, which not only protects data security but also improves system performance. First, a hierarchical task management method based on blockchain is designed to protect

TABLE XI
SUMMERY OF UAV-ASSISTED SENSING

Type	Ref.	Problem Formulation	Objective	Approach	Restrictions	Characteristic
Centralized Sensing	[220]	Task Coverage	Maximize sensing coverage	AC + PPO	Energy constraint + Cost constraint	Jointly schedule UAV nodes and MU nodes
	[221]	Task Allocation + Path Plan	Increase platform profits + Ensure task completion rates	DDQN	Eneray constraint	UAV package delivery scenario
	[222]	Path Plan	Maximize the total amount of data + Maximize geographical fairness + minimize UAV energy consumption	CNN + PPO	Energy constraint	Considering UAV charge scenario
	[223]	Path Plan	Increase data collection volume + Reduce space cost	CNN + DQN	Eneray constraint + Spatiotemporal constraint	Considering UAV charge scenario
Distributed Sensing	[224]	Path Plan	Maximize collect data amount + Ensure geographical fairness + Minimize energy consumption	Gated recurrent unit sequential + Distributed DRL	Eneray constraint + Delay constraint	Considering data freshness
	[225]	Path Plan	Maximize system utility	Multi-agent AC + Attention mechanism	Eneray constraint	Considering task offloading
	[226]	Path Plan	Effective data collection	MADDPG + Attention mechanism	Eneray constraint	Considering path overlap
	[227]	Path Plan	Maximize data collection amount + Maintain geographic fairness	CNN + MADDPG	Eneray constraint + Sensing range	Considering N-step return and priority experience replay
	[228]	Task Allocation	Improve data quality + Improve sensing coverage	Incetive mechaim + MADDPG	Coverage requirement + Budget constraint	Online scenario

task information. Then, a DRL-based privacy task assignment method is proposed. This method can dynamically select the block size, generation rules, consensus approach, and other strategies, thereby improving the system's performance.

[Others]

Vehicles travel on roads, and the road network can be modelled as a graph. When the road network is transformed into a graph, the problem of vehicle trajectory exploration can be transformed into the problem of searching the shortest path problem on the graph. Based on this theory, several scholars have conducted relevant research.

Xu *et al.* in [78] proposed a new framework and introduced a tripartite graph to model dynamic road networks. It can also reflect traffic flow and vehicle preferences compared to traditional connection diagrams. Here, a method based on entropy and flow of origin and destination is proposed to evaluate the importance of nodes. Then, a method for sorting intersections is proposed, which analyzes the relationship between paths and nodes through feature vectors. Sun *et al.* in [229] proposed a two-layer crowdsensing scheme for sensing data processing and optimization. In the path layer, a fog-assisted vehicle weighting graph is constructed, and a new path exploration strategy is proposed to improve the utilization rate of each vehicle. Due to the significant duplication of sensing data collected by vehicles, different tasks are assigned to vehicles in the data processing layer. Therefore, similar information on path nodes is filtered to reduce resource wastage.

D. UAV-assisted Sensing

In this subsection, the research on UAV-assisted sensing is introduced. As the sensing entity in the air, UAVs equipped with professional sensors, can move according to sensing needs. Typically, the flight trajectory of UAVs is the primary concern. By designing a reasonable flight trajectory, the completion rate of tasks can be optimized, the amount of data collected can be increased, and energy consumption can be reduced, etc. In particular, with the development of research related to crowd intelligence, it has been widely used in multi-UAVs scenarios. Specifically, DRL and distributed multi-agent DRL methods are applied in UAV-assisted sensing. Table XI summarizes the relevant research on UAV-assisted sensing.

1) Centralized Sensing: The centralized sensing means that the platform makes unified decisions on the actions of multiple UAVs based on the overall environment. Ding *et al.* in [220] jointly scheduled UAV nodes and MU nodes to cooperate to complete sensing tasks. First, the objective function is constructed considering UAV energy consumption cost, MU incentive cost, sensing coverage, geographical fairness, etc. Then, an AC-based heterogeneous collaborative RL method is proposed. The method expanded the state space by local observations, extracted the states of neighbouring nodes, and used a generalized model to ensure the stability of the network. Finally, the PPO is applied to avoid destructive policy updates. Tao *et al.* in [221] proposed a UAV-based sensing task assignment problem, with the goal of increasing platform profits while ensuring task completion rates. This problem is further formulated as a UAV trajectory planning problem, and a DDQN method combined with prioritized experience replay is proposed.

There are also studies that have formulated the joint UAV path planning and UAV charging problem. In [222], Liu *et al.* studied the problem of cooperative collection of sensing data by UAVs while considering the charging of UAVs from multiple random charging stations. The spatiotemporal data is modelled based on CNN, and a feature extraction module is applied. Then, a DRL method based on PPO is proposed to guide UAVs decisions making, including path planning deci-

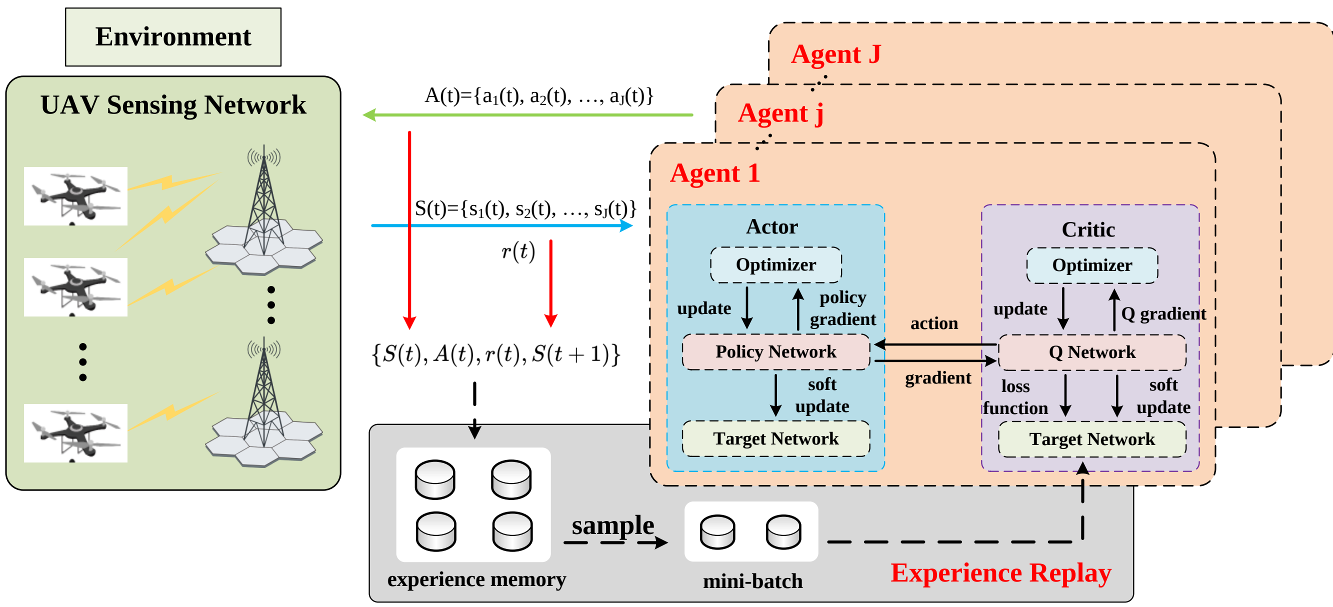

Fig. 16. The network structure of MADDPG in the UAV-assisted sensing scenario.

sions and charging decisions. In [223], Zhang *et al.* studied an efficient UAV control scheme for scheduling multiple UAVs. First, a control method based on DRL is proposed to control UAVs to collect high-priority sensing data in a restricted area. Then, a DRL-based UAV charging path decision method is proposed, so as to reach the charging station in a short time and optimize the space cost.

2) Distributed Sensing: Dai *et al.* in [224] proposed a distributed DRL method named DRL-eFresh, to achieve energy-efficient UAV-assisted sensing through distributed execution and centralized control. The GRU sequence is used to analyze the additional information of adjacent time slots, so as to better guide the actions of UAVs. By scheduling UAV trajectories, the goal is to achieve an optimal trade-off among energy consumption, data collection volume, and geographic fairness. Cai *et al.* in [225] proposed a UAV-based computation offloading and data sensing approach with the goal of maximizing system utility. First, the multi-objective utility function is defined according to the UAV trajectory selection and task strategy. Then, a multi-agent AC method is proposed to train the policy network. Due to the delay and energy consumption caused by the communication between UAVs, a centralized critic network is further trained to balance the strategies among multiple UAVs. Finally, an attention mechanism is introduced to improve the convergence performance of the model.

In particular, several studies have addressed the distributed UAV-assisted sensing problem based on the multi-agent DDPG (MADDPG) approach. Fig. 16 shows the network structure of MADDPG in the UAV-assisted sensing scenario. Wei *et al.* in [226] studied a DRL-based path planning method for building a high-performance UAV-assisted sensing system. The multi-UAVs path planning problem is formulated as a partially observable Markov decision process, Then, an attention mechanism is added to the AC network to assist UAVs in collecting data. Based on this, an improved MADDPG method is proposed for path planning of UAVs. In [227], Liu *et al.* proposed an energy-efficient distributed UAV-assisted sensing method, with the goal of increasing the amount of data collection and maintaining geographic fairness under energy consumption constraints. The CNN is integrated to extract features, and then the MADDPG method is applied for distributed execution to guide UAV decisions. In addition, N-step return and priority experience replay are introduced to obtain more optimal policies. Gao *et al.* in [228] studied UAV-assisted multi-task assignment, to improve data quality and sensing coverage. Here, an online incentive mechanism is designed to encourage UAVs to participate in sensing tasks, and a participant recruitment method considering data quality is proposed. Then, the MADDPG method is used to plan the trajectory of the UAV according to the real-time environment.

3) Timeline: Due to the rapid development of UAV-assisted sensing in recent years, this part introduces the temporal evolution of related research. Fig. 17 shows the occurrence time of related research in a graphical manner.

2015: Luo *et al.* in [230] studied the UAV sensing problem in disaster scenarios. A cloud-based UAV application architecture is proposed, which can solve some challenges faced by UAVs, such as network instability and resource constraints.

2016: Zhang *et al.* in [231] studied UAV-assisted participatory crowdsourcing systems. Through the professional sensors of UAVs, more reliable data can be collected. Collaboration between UAVs and human participants can reduce the cost of sensing and improve the reliability of sensing.

2017: In [232], authors investigated sensing data collection in cities by UAVs. By planning the trajectory of the UAV, the interaction time between the UAV and the user equipment is maximized. In this way, the collected data is delivered to the user.

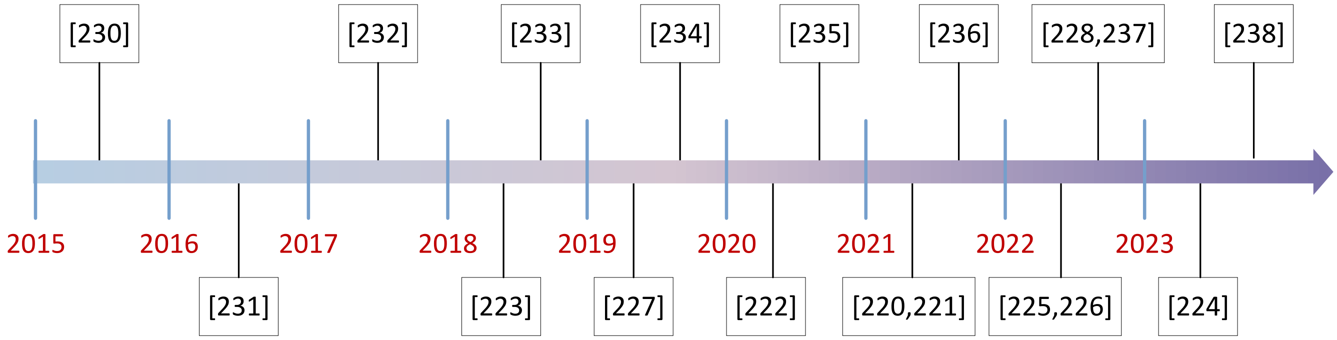

Fig. 17. The UAV-assisted sensing timeline.

2018: Zhou *et al.* in [233] studied the problem of route planning and task allocation for multiple UAVs. Under the constraints of energy consumption and time delay, the path planning problem is solved by dynamic programming and genetic algorithm. The task allocation problem is solved by the Gale-Shapley method. The goal is to maximize UAVs revenue while reducing energy consumption.

2019: Yang *et al.* in [234] studied the UAV-based urban air pollution monitoring problem, combining UAV and ground equipment for sensing. First, photos are taken in the air by UAVs and pollution data is collected by sensors on the ground. Then, computer vision technology is used to judge the data in the photo, and CNN is used for learning and speculation. The method can enable accurate air quality monitoring and future forecasting.

2020: In [235], authors investigated environmental monitoring through UAV-assisted sensing. An incentive mechanism is proposed to recruit UAVs for sensing. The goal is to maximize the sensing coverage.

2021: Wang *et al.* in [236] studied the safety framework in UAV-assisted sensing. First, a blockchain-based learning architecture is proposed for distributed model updating. Second, UAV personal information is protected through differential privacy. Finally, high-quality model sharing by UAVs is facilitated by RL.

2022: Recently, delivery drones have also been applied to urban sensing. Chen *et al.* in [237] studied crowdsensing based on delivery drones. By scheduling the flight trajectory of drones, more efficient delivery and sensing can be achieved. A DRL-based approach is proposed to address this problem, taking into account energy consumption constraints and resource availability.

2023: Xiang *et al.* in [238] studied the problem of urban sensing via delivery drones. Unlike traditional UAV-assisted sensing, this problem also needs to consider the influence of cargo weight. Therefore, under energy consumption constraints, authors jointly optimize path planning, sensing time and weight allocation. The goal is to maximize sensing utility while maintaining the weight of the cargo transported. Finally, approximate optimal solutions are obtained based on equivalent target construction, local search, and alternate iterations.

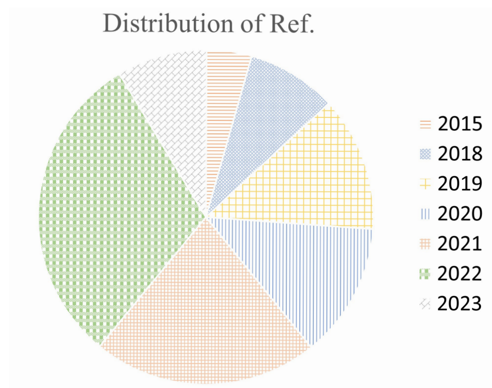

Fig. 18. The literature under vehicle-oriented applications.

E. Typical Applications for Vehicle-oriented Sensing

Related applications for vehicle-oriented sensing bring more convenience to social life. Specifically, we mainly introduce related applications from three aspects: map sensing, traffic monitoring, and infrastructure management. Table XII summarizes related applications for vehicle-oriented sensing. Meanwhile, Fig. 18 shows the literature years for vehicle-sensing applications based on our survey. In particular, with the development of smart cities, the application of vehicle-oriented sensing in high-precision map construction and traffic monitoring has shown great advantages.

1) Map Sensing: Nowadays, vehicles equipped with sensors that can better support map construction. Thanks to mobility and vehicles' route, map construction through distributed vehicle-oriented sensing can reduce platform overhead and provide timely updates.

Map Creation and Updates: Recently, researchers focus on global map creation and updating. Qi *et al.* in [31] studied a distributed vehicle sensing scheme for HD map updates. Here, real-time data is collected by vehicles, and the data is processed by onboard distributed computing to extract updated content to reduce data transmission. The data aggregation process is then centralized on the server, taking into account that the vehicle will drive out of the target area. Due to the differences in sensing capabilities of different vehicles, how to select vehicles and assign sensing tasks should also be considered. A heuristic approach is proposed to solve this problem, with the goal of reducing task overhead. Cao *et al.* in [239] studied the problem of crowdsourcing vehicle selection in high-definition maps, collecting and updating map data by vehicles. First, the GPS trajectories of two cities are analyzed, while appropriate vehicles are selected to maximize the platform's utility under budget constraints. The online worker selection problem is solved with a method based on upper confidence bounds.

Lane-level Map: Several studies focus on lane-level road information. Shu *et al.* studied lane-level map construction methods in [240]. This method can directly extract lane-level data from the GPS trajectories of crowdsourcing vehicles to complete the task accurately and efficiently. First, a technique for clustering and separating trajectories is presented by utilizing the discrete Fréchet distance and entropy theory. This method has the capability to handle pre-existing trajectories with high precision effectively. Then, an approach for extracting road information at the lane level is proposed, which employs the least square estimation-constrained Gaussian mixture model. Zhou *et al.* in [241] proposed a scheme to extract lane information by crowdsourcing vehicles. The vehicle records location information and road images while driving. Here, lane markings in an image are detected, and the location data is projected into 3D space. The cloud then discards abnormal data according to noise clustering and progressive fitting, to improve data accuracy. Through verification, the requirements of high-precision maps can be met, as a low-cost map update method.

Intersection Map: Several studies have focused on the establishment of intersections in road network maps. In [242], Yang *et al.* studied methods for generating lane-level intersection maps from crowdsourcing vehicle data. The intersections are first identified based on a spatial clustering approach. Then, the intersection layout is analyzed using a trajectory integration approach and road turning rules. Finally, the final intersection map is generated based on geometric matching methods based on the vehicle's road information and intersection layout detection information. Zhang *et al.* in [243] studied the problem of intersections generation from taxi trajectories. Here, road intersections in vector and raster space are first extracted. Then, multiple methods are combined to analyze the uneven distribution of vehicle trajectories. Finally, the turning relationship and direction information are analyzed according to the intersection state, such that the accuracy of the road network topology is maintained, while the road sections are repaired.

2) Traffic Monitoring: The vehicle-oriented sensing also has applications in traffic monitoring. Current traffic conditions can be sensed by analysing vehicle trajectories, and real-time traffic management can also be carried out. In addition, the condition of infrastructure can also be monitored by installing the appropriate sensors.

Traffic Condition: recently, many studies have estimated the traffic condition through vehicle sensing and then guided the driving route of vehicles. In [32], authors studied the vehicle sensing-based dynamic control method of traffic congestion. The traffic data is collected in real time by sensing vehicles without needing sensors on the road. By managing traffic flow based on traffic data, traffic jams can be avoided, while drivers' driving time can be reduced. In [244], Shao *et al.* investigated a data collection method considering the road network topology to estimate urban traffic conditions. First, the traffic conditions at the location of vehicles are calculated. Then the traffic conditions of unreached roads are estimated based on the correlation of adjacent roads. In addition, data collection is taken care of by the local vehicle, and data processing is taken care of by the server platform.

Traffic Management: With vehicle-oriented sensing, a real-time traffic management system can be established. This can not only quickly respond to emergencies on the road but also provide timely information feedback. Wang *et al.* in [245] studied real-time traffic management by optimizing content dissemination to reduce service response time. First, a sensing-based model is proposed to sense and report events in real-time, and provide timely traffic management responses. Then, according to the random theory, the transmission delay of message is estimated, the message forwarding process is optimized, and the efficiency is improved. In [246], Wang *et al.* studied the establishment of a real-time traffic management system based on vehicle sensing, to provide timely feedback on abnormal events that occur. In the scenario of heterogeneous social networking of vehicles, a model that supports D2D communication can be established, while information can be uploaded collaboratively to shorten the response time.

Infrastructure Monitoring: The infrastructure can be monitored in real-time through the distributed sensing method to prevent abnormal occurrences. In [247], authors studied three methods of transport infrastructure monitoring through crowdsourcing vehicles. First, mobile devices in vehicles are used to collect vibration data and detect damage to bridges. Then, the feasibility of gyroscopes for road detection is verified through realistic experiments, allowing for the measurement of road deformation. Finally, the condition of road surface is also assessed by means of an onboard camera. Authors in [248] investigated a sensing-based infrastructure monitoring scheme, to monitor infrastructure anomalies in real-time. A platform for managing vehicle sensing data is designed. This covers a database for storing sensing data, an integration method for analyzing data, and an interactive system for visualization. In addition, designing corresponding methods can achieve bridge damage detection, bridge frequency identification, and road crack detection.

Traffic Violation Detection: Through crowdsensing, traffic violations can be detected in real-time, and the route of inspectors can be guided to improve work efficiency. In [249], Jiang *et al.* studied the crowdsensing-based traffic violation information collection method and dynamically adjusted the patrol route. First, locations with a high frequency of traffic violations are inferred based on historical information, and traffic violation hotspots are judged based on an adaptive learning model. Then, according to the tensor-based modelling method, the optimal patrol route is provided to reduce the manpower cost. In [250], He *et al.* considered a shared bicycle-based parking violation detection scheme. First, the raw trajectories are processed and matched against the map. Then, characteristics are analyzed from the trajectory, and the

TABLE XII
SUMMARY OF APPLICATION FOR VEHICLE-ORIENTED SENSING

Applications		Ref.	Solved problems	Approach	Objective
Map Sensing	Map Creation and Updates	[31]	How to select vehicles and assign sensing tasks	Data aggregation + Heuristic approach	HD map update
		[239]	Crowdsourcing vehicle selection in high-definition map	Transfer learning + Upper confidence bounds method	Collect and update map data
	Lane-level Map	[240]	Directly extract lane level data from GPS trajectories to complete tasks	Discrete Fréchet distance + Entropy theory + Gaussian mixture model	Extracte road information at the lane level
		[241]	Extract lane information by crowdsourcing vehicles	Noise clustering + Progressive fitting	Low-cost map update + High-precision map
	Intersection Map	[242]	Generate lane-level intersection maps from crowdsourcing vehicle data	Spatial clustering + Trajectory integration approach + Geometric matching	Generate intersection map
		[243]	Generate intersections from taxi trajectories	Clustering + Intersection fusion mechanism	Ensure the integrity and accuracy of road intersections and road networks
Traffic Monitoring	Traffic Condition	[32]	Vehicle sening-based dynamic control of traffic congestion	Dynamic traffic efficiency framework + Dynamic path allocation	Avoide traffic congestion + Reduce driver's driving time
		[244]	Address the efficiency and effectiveness of traffic condition assessment based on vehicle sensing data	Two stage vehicle data collection method + Sponsors-followers program	Estimate urban traffic conditions
	Traffic Management	[245]	Sensing based real-time traffic flow management	Clustering + Random theory + Delay sensitive routing algorithm	Optimize message forwarding process + Improve efficiency
		[246]	Establish a real-time traffic management system based on vehicle sensing	Heterogeneous traffic management method	Provide timely feedback on traffic anomalies
	Infrastructure Monitoring	[247]	Transport infrastructure monitoring using vehicle sensors	Bridge damage detection method + Gyroscope and motion camera monitoring	Efficient and low-cost monitoring
		[248]	Monitor infrastructure anomalies in real-time	Establish software platform + Three detection methods	Reduce costs + Improve efficiency
	Traffic Violation Detection	[249]	Crowdsourcing sensing-based traffic violation information collection	Adaptive learning model + Tensor-based modelling method	Reduce manpower cost
		[250]	Shared bicycle-based parking violation detection	Distribution test method + Trajectory matching	Improve detection efficiency
Infrastructure Management	Road Detection	[33]	Collecting road surface data using connected vehicles	Estimate roughness index + Reconstruct road condition	Timely acquisition of road surface data + Improve road network coverage
		[251]	Evaluate road roughness through vehicle sensing	Majority voting method	Guide choose high comfort route
		[252]	Avoide the impact of sparse labels on data analysis	Cloud-edge-end manner + Active learning + Comfortable route planning method	Identify road damage + Provide comfortable navigation
	Parking Space Detection	[253]	Search for parking spaces through crowdsourcing vehicles	Monocular RGB camera + Vision-based tracking mechanism + Map matching	Identify unparked parking spaces
		[254]	Guidance on the availability of future parking spaces	Logistic regression + Incentive method	Attract more participants
	Air Monitoring	[255]	Monitor air quality through vehicle sensing	Evolution method	Reduce platform cost + Improve spatiotemporal coverage
		[256]	The impact of transportation on air quality in designated areas	Mobile air quality monitoring system	Reconstruct the temporal and spatial distribution of pollutants in the air
	Disaster Management	[257]	Dynamic sensing through UAV in disaster relief scenarios	Multi-waitlist-based approach + Stable matching	Recruit UAVs to achieve stable task matching
		[258]	Using UAV to achieve information sharing in disaster relief scenarios	Blockchain + Reputation protocol + Incetive method	Motivate UAVs and vehicles to participate in tasks

location of illegal parking is found by the method of distribution test. Combined with the detection results, the patrol personnel can be dynamically guided, which can effectively improve work efficiency.

3) Infrastructure Management: Vehicle-oriented sensing can serve social life and provide convenient solutions. It can not only effectively manage infrastructure, such as road detection, parking space detection, etc. It can also provide convenient management methods for social life, such as air detection, disaster management, etc.

Road Detection: Several studies have focused on detecting road conditions using vehicle-oriented sensing. Here, the damage to the road surface can be detected and repaired in a timely manner by means of vehicle-oriented sensing. By maintaining good road conditions, driving comfort can be improved, and road safety can be enhanced. Chen *et al.* in [33] collected road data through vehicle-oriented sensing. By analyzing the collected road surface information, the roughness of road surface can be estimated. Vehicles are connected to the cloud, where data is aggregated and processed to reconstruct road conditions. In addition, accidents on the road can also be inferred based on onboard sensor information.

Authors in [251] investigated a vehicle sensing-based scheme for road roughness assessment. Here, the influence of vehicle effects is first eliminated. Then, the road surfaces are ranked according to a majority voting method, while the roads are compared according to their quality. Finally, the roughness of the road surface can be analyzed, and passengers can be guided to choose a route with high comfort. Chen *et al.* in [252] studied a vehicle sensing-based scheme for identifying road damage, and providing comfortable navigation for vehicles. First, the autonomous cars in the city are regarded as sensing participants, and the road surface damage data is collected in a cloud-edge-end manner. Then, a model for accurately identifying pavement damage is proposed, and the problems caused by sparse labels can be avoided through active learning. Finally, a comfortable route planning method and a road damage evaluation model are proposed, according to the road damage situation.

Parking Space Detection: Several researchers have detected vacant parking spaces by means of vehicle sensing. In [253], authors studied crowdsourcing vehicle-based parking space search methods. Surrounding vehicles are sensed and monitored, by installing a monocular RGB camera on the vehicle and a vision-based tracking mechanism. It is then matched against the map to identify unparked parking spaces. Shi *et al.* in [254] studied a crowdsensing-based parking space monitoring scheme. The solution not only aggregates information such as on-street parking spaces and corresponding time prices in a timely manner and sends them to drivers, but also provides drivers with guidance on the future availability of parking spaces. Then, a method based on logistic regression is proposed to evaluate the future availability information of parking spaces. In addition, an incentive method is proposed to determine the incentive level according to the reliability and professionalism of the vehicle to attract more participants.

Air Monitoring: Vehicles move on the road can be used to monitor the real-time air environment in different places. Authors in [255] studied the air quality monitoring method based on vehicle sensing. The method can monitor air quality through vehicles, and the goal is to reduce platform costs while improving spatiotemporal coverage. Then, the monitoring frequency of the vehicle is determined according to the evolution method, while the optimal solution can be obtained. Authors studied air quality monitoring through vehicle sensing in [256]. Through the vehicle sensor network, the regional particulate matter values measured by each vehicle at its location are sent to a centralized platform. The platform can then reconstruct the temporal and spatial distribution of pollutants in the air from these data. Moreover, the method can be combined with professional monitoring by public institutions.

Disaster Management: In disaster scenarios, vehicles cannot reach the areas that need to be sensed due to damaged roads. Therefore, UAVs can be used as aerial sensing devices to reach the disaster area without being affected by ground traffic. Wang *et al.* in [257] studied an UAV-assisted sensing scheme for disaster relief networks. Here, UAVs are recruited for sensing tasks in random and dynamic environments, thus dynamic matching is accomplished. Then, a multi-waitlist-based approach is proposed to achieve a stable matching state in a dynamic environment. Wang *et al.* in [258] studied the information-sharing method in UAV-assisted disaster relief, where the information in disaster scenarios is protected through the blockchain. Here, honest actions by UAVs are facilitated through a reputation protocol. Ground vehicles are also used to assist UAVs in task calculations, and to motivate both UAVs and vehicles to participate in sensing tasks.

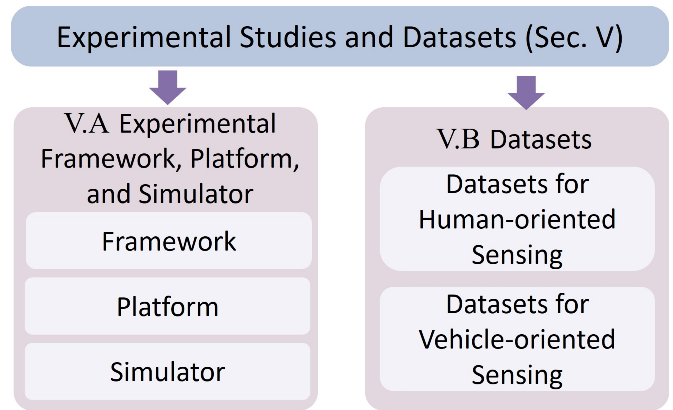

Fig. 19. The structure of section V.

V. Experimental studies and datasets

In this section, we first present the framework, platform, and simulator for crowdsensing. Then, we discuss the relevant datasets used for simulation experiments, divided into those for human-oriented sensing and vehicle-oriented sensing. Fig. 19 shows the structure of this section.

A. Experimental Framework, Platform, and Simulator

MCS systems should be implemented on a comprehensive architecture across mobile devices or computing platforms, to facilitate research and applications. This provides broad support for application developers and terminal users. Therefore, we categorized frameworks, platforms, and simulators as summarized in Table XIII.

[Framework]

In the crowdsensing-based framework research, including supporting heterogeneous sensing systems [259], [260], ensuring sensing safety [261], [262], supporting vehicle sensing [263], and programming frameworks [264].

1) CrowdManager: In [259], Liu *et al.* proposed a system framework named CrowdManager that can support the interaction and management of heterogeneous crowd agents in heterogeneous sensing systems. The framework includes three modules: information extraction and representation module, construction and management module, and communication and interaction module. It can realize rich interaction functions of heterogeneous crowd agents, while reducing communication time and resource occupancy.

2) CrowdOS: Liu *et al.* proposed a system called CrowdOS in [260], running on the abstract software layer between the original system and the application layer. The system consists of three frameworks: task analysis and allocation,

TABLE XIII
FRAMEWORKS, PLATFORMS, AND SIMULATORS

Type	Name	Ref.	Description
Framework	CrowdManager	[259]	It supports the interaction and management of heterogeneous crowd agents in heterogeneous sensing systems.
	CrowdOS	[260]	It runs on an abstract software layer between the original and application layers.
	FIRST	[261]	It optimizes information security in MD-based crowdsourcing sensing.
	VIVO	[262]	It is a sensing-based data collection framework that guarantees data security and privacy.
	P-ACP	[263]	It is a parallel vehicle crowdsensing framework that can handle high-complexity optimization processes.
	Medusa	[264]	It is a crowdsensing programming framework that executes in a distributed manner on smartphones.
	SILF	[265]	It is based on the smartphone's inertial learning framework to determine the vehicle's position.
Platform	Vita	[266]	It is a mobile cyber-physical system for crowdsensing applications, combining a service-oriented framework with resource optimisation theory.
	A3Droid	[267]	It provides sensing application development for the Android platform.
	Smart Agora	[268]	It is a platform that supports a flexible and modular crowdfunding architecture and can cope with a variety of complex outdoor experiments.
	ParticipAct	[269]	It collects practical information and guides participant behaviour. It also enables rapid mass deployment and reduces resource use by MDs.
	CARDAP	[270]	It is a distributed and scalable general-purpose platform and is applied to data analysis for sensing applications.
	CrowdTracker	[271]	It is a crowdsensing-based object-tracking system that tracks the trajectory of objects and predicts movement routes.
Simulator	CASC	[272]	It is a simulation environment for analysing crowdsensing-based applications in smart cities.
	CrowdSenSim	[273]	It is a crowdsensing simulator for simulating sensing activities in urban environment.
	CrowdSenSim 2.0	[274]	It is a hybrid sensing simulator with improved CrowdSenSim and is optimized in terms of time and performance.
	CATLES	[275]	It is an outdoor environment simulator for evaluating and testing context-aware systems in realistic scenarios.
	Ns-3	[276]	It simulates, models and analyzes the performance of crowdsensing networks.

centralized management of resources, and quality optimization of perceived results. Finally, a deep feedback framework based on human-computer interaction is proposed to evaluate the system's usability.

3) FIRST: Authors in [261] proposed a framework called FIRST to optimize information security in MD-based crowdsensing. The reliability of sensing data is assessed by trusted actors, with consideration on the number of participants to achieve classification accuracy. The proposed scheme is verified on the iOS and Android platforms, which can significantly reduce the impact of security attacks and ensure data reliability.

4) VIVO: In [262], authors proposed a crowdsensing-based data collection framework called VIVO with guaranteed data security and privacy. The system can use various IoT services, while the collected data can be accessed in real time at the end of the task. Furthermore, the system is deployed and run on participants' mobile phones, its performance is verified through practical applications.

5) P-ACP: Ren *et al.* in [263] proposed a framework for parallel vehicle crowdsensing. By introducing ACP-based parallel intelligence into the framework, high-complexity optimization processes can be tackled. The ACP approach is artificial society, computational experimentation, and parallel execution. According to these three steps, the influence of various external factors can be considered comprehensively for decision-making optimization.

6) Medusa: Authors in [264] proposed a programming framework for crowdsensing called Medusa. The high-level abstractions provided by this framework are necessary to accomplish sensing tasks, as performed in a distributed fashion on smartphones. Furthermore, multiple sensing tasks have been practically deployed, with completion results demonstrating low overhead and low complexity.

7) SILF: Tong *et al.* in [265] proposed a smartphone-based inertial learning framework to judge the position of vehicles. First, the limitations and technical difficulties of existing platforms are analyzed. Then, vehicle dynamics are studied based on the inertial parameters of the mobile phone, with model training to a temporal convolutional network for position inference. Finally, the collection of data set content is realized in the real scenario, and it is verified that the method can outperform traditional methods.

[Platform]

Among the crowdsensing-based platforms, there are application development platforms [266], [267], verification platforms for MD [268], [269], [270], and location tracking platforms [271], [265].

1) Vita: In [266], Hu *et al.* proposed a system called Vita, a mobile cyber-physical system for crowdsensing applications. It can enable MU to participate in sensing tasks effectively. Vita combines a service-oriented framework with resource optimization theory, to provide a flexible framework and achieve flexible deployment. It is proven by experiments that the system can finish the task efficiently and keep the cost low. In addition, a corresponding application is developed and deployed on Android devices to demonstrate the actual functionality.

2) A3Droid: Authors proposed a framework called A3Droid in [267], which provides sensing application development for the Android platform. Based on this, scalable applications can be developed on Android devices, and high-quality sensing data can be collected through MDs. Then, the feasibility of the application is verified by simulating the scenario, collecting location information on the bus, and analyzing relevant traffic information.

3) Smart Agora: In [268], authors presented a platform called Smart Agora, which is used in outdoor experiments. The platform supports a flexible modular architecture for crowdsensing and can cope with various complex scenarios. Experiments are also deployed on MU's smartphones to collect sensing data and reduce privacy costs.

4) ParticipAct: Authors in [269] established a platform called ParticipAct with the corresponding living laboratory. The experiment involved more than 170 participants who participated in a year-long sensing task. The tasks accessed information gathered by the sensors of MDs and guided the behaviour of participants. It is verified that the platform can achieve rapid large-scale deployment and reduce the resource usage of MDs.

5) CARDAP: Authors in [270] proposed a distributed and scalable general-purpose platform named CARDAP, which can be applied to data analysis for sensing applications. The platform draws on multiple energy-efficient transmission strategies and incorporates motion recognition for MUs. Application models in typical scenarios are then developed to evaluate the platform. Its cost estimation model and benefits are validated in terms of resource utilization, energy consumption, and task processing rate.

6) CrowdTracker: Jing *et al.* in [271] proposed a crowdsensing-based object tracking system named CrowdTracker. The object's trajectory is tracked by recruiting participants to take photos, and the movement route is predicted. In addition, real-time tracking can be achieved, and task costs for participants can be reduced. The historical vehicle trajectory can be analysed through the target motion prediction model and task assignment method, while the target's future position can be predicted. The effectiveness is verified by real datasets.

[Simulator]

The scarcity of large-scale real-life sensing data can sometimes hinder the construction of platforms. To overcome this limitation, simulators are used to demonstrate the feasibility or effectiveness of designed crowdsensing frameworks by using simulated data as input.

1) CASC: Authors in [272] studied a simulation environment for analyzing crowdsensing-based applications in smart cities. The parking scene is analyzed as a case, and the corresponding application is given to analyze the problems related to urban parking. The case results show that considerable benefits can be achieved with a lower number of users.

2) CrowdSenSim: Authors in [273] proposed a crowdsensing simulator called CrowdSenSim to simulate sensing activities in urban environments. It can analyze large-scale real-world environments, to support opportunistic and participatory sensing. Furthermore, through this simulator, the effectiveness of data collection and user recruitment can be studied. Through verification, excellent performance is achieved and can support the essential services of smart cities.

3) CrowdSenSim 2.0: Authors in [274] extended the original CrowdSenSim and proposed a simulator called CrowdSenSim 2.0, which can be used for hybrid mobile crowdsensing. State simulation, spatial coding, flexible task generation, and integration of user trajectory determination methods are supported. Computing capabilities are also optimized through code refactoring and parallel computing, to support the asynchronous operation of algorithms. Furthermore, the simulator is optimized in terms of time and performance.

4) CATLES: In [275], authors proposed an outdoor environment simulator called CATLES for evaluating and testing context-aware systems in realistic scenarios. It can simulate the position of the MD, by interactively controlling the virtual 3D. In addition, the background that the sensing application on the corresponding MD needs to sense is simulated by public WiFi and cell measurements.

5) NS-3: Authors in [276] proposed the NS-3 network simulation platform, which can simulate, model, and analyze the performance of crowdsensing networks. The sensing function of the MU is simulated, according to the mobility and wireless communication characteristics of the simulator.

B. Datasets

In partial literature, various platforms have been used to generate diverse datasets. Some focus on user location and social relationships, while others focus on the spatiotemporal trajectory information of vehicles. These datasets provide the basis for researchers to evaluate the presented solutions. Table XIV summarizes the relevant datasets.

[Datasets for Human-oriented Sensing]

In this part, we introduce related datasets for human-oriented sensing. These datasets have been widely used in several research.

TABLE XIV
RELATED DATASETS

Type	Name	Link	Description	Ref.
Datasets for Human-oriented Sensing	Yelp Dataset	https://www.yelp.com/dataset.	It contains more than 1 million pieces of information for multiple businesses reported by nearly 200,000 users.	[139], [277]
	Facebook Social Dataset	https://gitee.com/luozhuangye/mtsf/blob/master/data.csv	It includes features such as node characteristics and social relationships, with a total of 4039 nodes and 88234 edges.	[278], [279]
	Gowalla Dataset	http://snap.stanford.edu/data/loc-gowalla.html	It contains the user's location and social network features, and consists of 196,591 nodes and 950,327 edges.	[102], [100], [277]
	D4D Dataset	http://www.d4d.orange.com	It contains detailed geographic coordinates of cell towers, as well as phone call logs of about 50,000 individual users.	[100], [119], [145]
	StudentLife Dataset	http://studentlife.cs.dartmouth.edu/	It contains information collected from the mobile phones of 49 students over a 10-week period.	[108], [160]
	Check-In Dataset	——	It contains 490,000 records for the city of Chengdu, including addresses and address-related information.	[136]
	Brightkite Dataset	http://snap.stanford.edu/data/loc-brightkite.html	It includes 58,228 nodes and 214,078 edges, representing social network connections between users on the platform.	[131], [279], [280]
	Foursquare Dataset	https://archive.org/details/201309_foursquare_dataset_umn	It contains 2,153,471 users, 1,143,092 places, 1,021,970 check-ins, 27,098,490 social connections, and 2,809,581 ratings assigned to places by users.	[83], [280]
Datasets for Vehicle-oriented Sensing	Roma Taxi Dataset	https://crawdad.org/roma/taxi/20140717	It contains the GPS trajectories of 320 taxis, collected at 7-second intervals during the month of February 2014.	[117], [191], [246]
	San Francisco Taxi Dataset	https://crawdad.org/epfl/mobility/20090224	It contains the GPS coordinates of nearly 500 taxis in San Francisco, recorded for 30 days.	[141], [39], [261]
	Beijing Taxi Dataset	——	It contains the taxi travel records of about 20067 taxis in Beijing.	[58]
	Geolife Dataset	http://research.microsoft.com/en-us/downloads/b16d359d-d164-469e9fd4-daa38f2b2e13/	It contains the trajectories of 182 users over a five-year period from April 2007 to August 2012.	[37], [52], [141]
	Chicago Taxi Driving Dataset	https://data.cityofchicago.org/Transportation/Taxi-Trips-2013/6h2x-drp2	It contains taxi trajectories in Chicago, spanning from 2013 to 2016.	[88]
	Chengdu Taxi Trajectory Dataset	——	It contains about 13600 taxi routes, about 80 million GPS points, recorded for 15 days.	[119], [249], [271]
	Seattle Bus Dataset	——	It contains the trajectories of approximately 750 buses in Seattle.	[80], [180]
	Xiamen Taxi Dataset	——	It contains the trajectory data of about 5,000 taxis in Xiamen, China, about 220 million GPS location records and 8 million real-time trips in July 2014.	[189], [249]
	Cologne Dataset	——	It contains 24-hour vehicle data within 400 square kilometres of Cologne and surrounding areas in Germany.	[176], [281]

1) Yelp Dataset [139], [277]*:* Containing over a million properties of multiple businesses reported by nearly two hundred thousand users, Yelp is a social network dedicated to business directory and review services. Typically, participants and workers can be randomly selected to join the experiment based on the characteristics of data in Yelp and include their task characteristics.

2) Facebook Social Dataset [278], [279]*:* This dataset can be used to model the relationship between agents and users in social networks. The network covers characteristics such as node characteristics and social relations, has a total of 4039 nodes and 88234 edges.

3) Gowalla Dataset [102], [100], [277]*:* This dataset is a location-based social network containing the user's location and social network characteristics. The social network is undirected, consists of 196591 nodes and 950327 edges. Generally, nodes are randomly selected in these data to form a sub-network for performance analysis.

4) D4D Dataset [100], [119], [145]*:* The D4D dataset comprises two distinct categories of data entries about the Ivory Coast. The first category contains details concerning cellular towers, to encompasses their unique identification numbers and geographical coordinates regarding latitude and longitude. The second category comprises phone call records of around 50,000 individual users.

5) StudentLife Dataset [108], [160]*:* The StudentLife dataset, made available by researchers at Dartmouth College, was compiled by gathering information from the mobile phones of a group of 49 students over a period of 10 weeks. This dataset includes a variety of data readings, such as GPS and WiFi signals, among others.

6) Check-In Dataset [136]*:* The Check-In dataset comprised 490,000 records was compiled in Chengdu, Sichuan, China. Each check-in record includes details such as the address, longitude, and latitude of the check-in location, along with information regarding the type of location (e.g., school, bank, restaurant, etc.). These check-in points accurately represented the distribution of sensing locations throughout the city, providing valuable insights into urban mobility patterns and human behaviour.

7) Brightkite Dataset [131], [279], [280]*:* Brightkite is a popular social network platform that enables users to share their location-based check-ins. The dataset comprises 58,228 nodes and 214,078 edges, representing the social network connections between users on the platform.

8) Foursquare Dataset [83], [280]*:* This dataset contains 2153471 users, 1143092 locations, 1021970 check-ins, 27098490 social relationships, and 2809581 ratings assigned by users to locations. All of these are extracted from the Foursquare application through a public API. All user information is anonymous, i.e. the user's geographical location is also anonymous. Each user is represented by an ID and GeoSpatial location.

[Datasets for Vehicle-oriented Sensing]

In this part, we introduce related datasets used for vehicle-oriented sensing. New algorithms and models can be developed and tested for a variety of applications, including autonomous driving, traffic forecasting, and traffic planning.

1) Roma Taxi Dataset [117], [191], [246]*:* The dataset known as Roma Taxi encompasses the mobility traces of nearly 320 taxis operating within the central area of Rome. This dataset entails the GPS coordinates of each taxi, which are recorded at intervals of 7 seconds throughout one month in February 2014. Drivers of the taxis are equipped with tablets, so as to periodically gather positional data and transmit this information to the central server.

2) San Francisco Taxi Dataset [141], [39], [261]*:* This dataset comprises the mobility traces of taxi cabs operating within the San Francisco Bay Area in the United States of America. The dataset includes GPS coordinates of nearly 500 taxis, documented over a duration of 30 days. Each taxi is equipped with a system that periodically sends its location details to the central server, including information such as timestamp, identifier, and geo-coordinates. The average time interval between two consecutive location updates is recorded within less than 10 seconds.

3) Beijing Taxi Dataset [58]*:* The dataset encompasses records of taxi trips undertaken by approximately 20,067 taxis operating within the city of Beijing, one of China's largest cities. This dataset documents a period of one month, and each record included within it comprises essential details such as taxi ID, time, location (expressed in terms of longitude and latitude), and occupancy status (indicating whether the taxi is occupied by one or more customers). Each taxi is programmed to collect one record every minute while in operation.

4) Geolife Dataset [37], [52], [141]*:* The dataset in question comprises data collected by the GeoLife project conducted by Microsoft Research Asia, documenting the trajectories of 182 users over a period of more than five years, starting from April 2007 and ending in August 2012. Each GPS trajectory contained within this dataset is represented as a record consisting of time-stamped location details, including information related to latitude, longitude, altitude, and other relevant attributes. The dataset includes a total of 17,621 trajectories, documenting a total distance of 1,292,951 kilometres and a cumulative duration of 50,176 hours.

5) Chicago Taxi Driving Dataset [88]*:* The dataset pertains to taxi rides in Chicago, spanning the time period between 2013 to 2016. Along with various ride-related details such as travel time and itinerary, this dataset also encompasses several attributes related to taxis themselves, such as timestamp, taxi ID, and location in terms of latitude and longitude.

6) Chengdu Taxi Trajectory Dataset [119], [249], [271]*:* The dataset concerning taxi trajectories comprises a comprehensive collection of around 13,600 taxi routes, documenting a period of 15 days. In addition, this dataset includes a massive amount of data, containing roughly 80 million GPS points.

7) Seattle Bus Dataset [80], [180]*:* The Seattle bus trace dataset was compiled by collecting data from around 750 buses. These buses traverse different routes located in Seattle, USA, over several weeks. This dataset documents the movements of the buses as they travel through the city, and contains information related to their location, speed, and other relevant parameters.

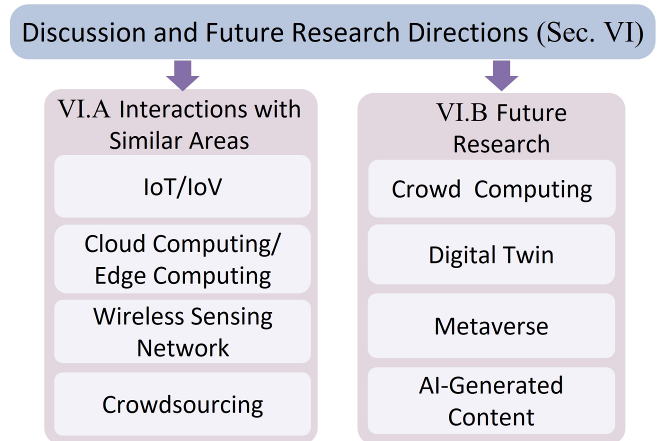

Fig. 20. The structure of section VI.

8) Xiamen Taxi Dataset [189], [249]*:* The Xiamen taxi dataset contained the trajectory data of approximately 5,000 taxis in Xiamen, China, in July 2014. This dataset comprises approximately 220 million GPS position records and 8 million live trips, providing a detailed picture of taxi movement and usage patterns in the city.

9) Cologne Dataset [176]*:* Authors in [281] proposed a dataset based on vehicle movement data, taking into account both the macro and microstate of the road. This dataset covers 24 hours of car data within 400 square kilometres of Cologne and surrounding areas in Germany. Authors described the process of generating this dataset and presented improvements to the dataset for existing datasets.

VI. Discussion and Future Research Directions

In this section, we first discuss similar areas related to crowdsensing. Then, we discuss the development trends and possible future research directions of crowdsensing. Specifically, we analyze the combination of the three directions of crowd computing, digital twin, and metaverse. These have pointed out the direction for the future development of smart cities. Fig. 20 shows the structure of this section.

A. Interactions with Similar Areas

Several other areas are closely related to crowdsensing and have played an essential role in developing smart cities. In this subsection, the relevant areas are described. Fig. 21 shows the relevant areas of crowdsensing.

1) IoT/IoV: The Internet of Things (IoT) connects any object to the network through information-sensing devices [282]. The objects exchange and communicate information through an information dissemination medium to achieve various intelligent functions. In crowdsensing, devices with sensors also transmit data to each other, so it can be seen as an application in the IoT. In fact, some IoT devices can be directly used as sensing devices and participate in sensing tasks. This integration can bring advantages without consuming additional costs. For example, in indoor sensing scenarios, IoT devices such as net-connected cameras and routers can participate in

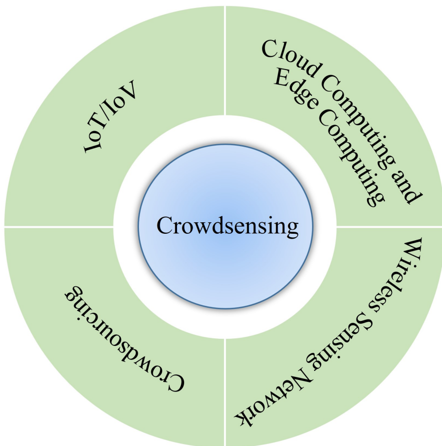

Fig. 21. The related areas of crowdsensing.

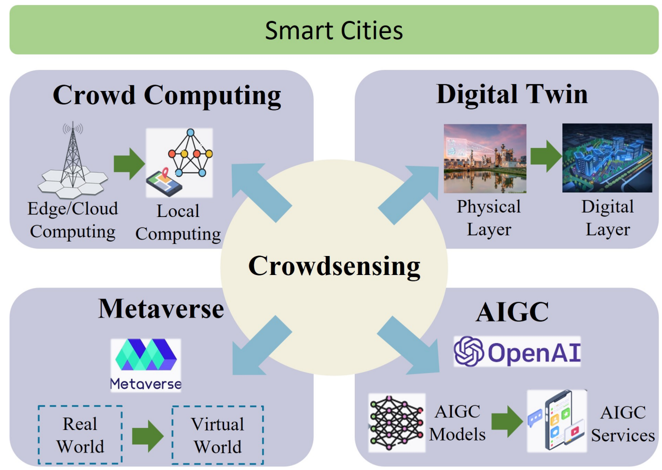

Fig. 22. The future research of crowdsensing in smart cities.

sensing tasks through their own sensing capabilities without additional costs.

Similarly, the IoV revolves around the vehicle as the primary subject, representing an extension of IoT technology into transportation [283]. With the increasing intelligence of vehicles, incorporating various onboard sensors has brought significant changes to crowdsensing [284]. Vehicles can perform multiple tasks such as sensing, transmission, and computation, thus expanding the potential application scenarios for crowdsensing. In addition, the IoV provides richer communication modes: Vehicle to Vehicle (V2V), Vehicle to Road side unit (V2R), etc. This makes VCS have more sensing forms and stronger sensing ability. Since the trajectories of most vehicles are regular, it is also easier to predict them, leading to a reasonable allocation of sensing tasks.

2) Cloud Computing and Edge Computing: Generally, after completing the sensing task, the analysis and processing of sensing data may consume a lot of computing resources. Due to the limited computing power of MDs, it may not be able to be completed locally. Cloud computing can reduce the computational pressure of MD by uploading sensing data to the cloud for processing [285]. In crowdsensing, the platform responsible for task distribution and collection is usually deployed on the cloud. Utilizing the powerful computing power of cloud, sensing tasks can be efficiently processed. Furthermore, with cloud-centric sensing, the platform can analyze global information, making the allocation and processing of sensing tasks more rational and efficient.

However, cloud computing also faces several problems. Since the cloud is deployed far from MUs, data transmission may require a significant latency, which may be unacceptable for some latency-sensitive tasks [286]. Hence, edge computing is introduced. Edge computing is to migrate the computing power and resources of cloud to a location close to the user. In this way, the delay and additional overhead that may be caused by long-distance transmission can be avoided [287]. In delay-sensitive sensing procedures, the sensing data can be transmitted to the edge server for processing, enabling the task requester to receive the sensing results in a timely manner [288]. For example, edge computing can easily meet the requirements of vehicles that need location-based sensing services with low latency.

3) Wireless Sensing Network: Wireless Sensor Network (WSN) is a distributed sensing network in which sensors communicate with each other through wireless connections [289]. WSN is also a way of data collection. The sensing data it produces exhibits high accuracy and stability, rendering it a dependable data source for data verification purposes. However, it has problems such as high maintenance costs and difficult expansion. Unlike traditional WSN, each sensing device in the crowdsensing system can directly communicate with the platform. Its advantage is that it saves the cost of deploying and maintaining sensor nodes. In addition, it also reflects the high scalability of system and the versatility of tasks to be completed.

4) Crowdsourcing: The concept of crowdsourcing was first proposed by Jeff Howe in 2006. It is a novel technology that facilitates both active and passive engagement of individuals in task completion. As a new business model, crowdsourcing enables people to use the crowdsourcing platform on the Internet to assign tasks, seek ideas or solve technical problems [290]. Analogous to crowdsensing, crowdsourcing requires platforms to recruit workers to complete tasks. In effect, crowdsensing is a new data acquisition model that combines the idea of crowdsourcing and relies on the sensing capabilities of MDs.

B. Future Research

Recently, typical emerging technologies are promoting the construction and development of smart cities. This brings a new development direction for crowdsensing in smart cities. The combination of these emerging technologies can better play the role of crowdsensing in smart cities. Fig. 22 shows the future research of crowdsensing in smart cities.

1) Crowd Computing: Crowd Computing is a new collaborative computing paradigm for heterogeneous agents in human-machine-object fusion environments. This concept was first proposed by Guo *et al.* in [17]. In the field of crowd computing, its core lies in "crowd" and "intelligence". The "crowd" here refers to a group composed of MDs, UAVs, vehicles, or their mixtures [291]. "Intelligence" refers to the sensing ability and autonomous intelligence possessed by these crowds. In crowd computing, these crowds can work together, and cooperate with each other, using their sensing and intelligence capabilities to solve various problems. For example, in a vehicle crowd scenario, each vehicle can perform different tasks and work more efficiently by exchanging information [292]. Therefore, the goal of crowd computing is to improve the efficiency, security, and reliability of the system, by combining the capabilities of various smart devices. In general, the first research direction is to combine crowd computing with existing sensing scenarios. In this way, the coordinated scheduling and performance improvement of participants' complementary resources/capabilities can be realized.

In the current scenario, the participants complete the sensing task and upload the task results to the platform (server) for result analysis. A large amount of sensing data is submitted to the platform, which not only easily leads to security issues of data leakage but also may cause inevitable transmission and calculation delays. Here, crowd computing brings new development opportunities for crowdsensing scenarios [293]. With the improvement of the computing power of MDs, sensing tasks can be performed in a distributed manner on the device side. The sensing results are then directly uploaded to the platform and sent to the requester. In addition, heterogeneous devices can perform collaborative processing and computing through D2D.

Moreover, in order to protect data security, the idea of federated learning can be introduced to protect the privacy of sensing data on the device side. For instance, Zhao *et al.* in [294] investigated a privacy-preserving crowdsensing system named CrowdFL. Integrating federated learning into crowdsensing can not only protect the privacy of participants, but also make full use of the computing power of participants. In addition, the performance and efficiency of the system can be improved.

Certainly, the application and development of crowd computing still face several problems, which will need to be addressed in future research [295]. The challenges faced by crowd computing in terms of mechanism, model, method, and platform mainly involve the following three aspects:

(1) Non-deterministic: Due to the cross-domain interweaving involving multiple heterogeneous actors, their interactions, relationships, and aggregation outcomes present uncertainty. Therefore, it is necessary to construct deterministic models or rules to achieve effective regulation of sensing results.
(2) Evolvability: Heterogeneous participants face differences in computing capabilities and the complexity of computing scenarios. Therefore, it is necessary to construct an adaptive evolution crowd computing model and formal verification method. In this way, the coordinated scheduling and performance enhancement of participants' complementary resources/capabilities can be realized.
(3) Assurance: Heterogeneous participants can gather dynamically, but their service requirements also face diversity. Thus, crowd collaboration differs widely from the accuracy and completeness of decision-making. Therefore, it is necessary to design a suitable quantitative evaluation system and method to support high-quality crowd computing services effectively.

2) Digital Twin: The Digital Twin (DT) refers to the use of digital technology and simulation technology to model physical objects or systems in virtual space. In this way, real-time monitoring and prediction of physical objects or systems can be realized. The definition of DT is formally presented in [296]. The definition comprised three key components: physical objects in the physical space, virtual objects in the virtual space, and the data connection between these two spaces [297]. In recent years, DT has garnered significant attention for its applications across various domains, including intelligent transportation systems, 6G networks, and smart cities [298].

Specifically, DT has broad application prospects in intelligent transportation systems and smart cities [299]. Crowdsensing also has applications in the above fields, so they can be combined with DT to take advantage of each other. From a technical point of view, the application of DT in smart cities covers three levels of "cloud-network-terminal" [300]. A comprehensive support system for smart cities with data-driven decision-making and technology integration has been formed. On the terminal side, DT realizes crowdsensing and visual control. On the network side, DT realizes the integrated network connection of air, space, and ground. On the cloud side, DT realizes the computing power of on-demand scheduling and iterative learning.

Generally speaking, on the terminal side, DT needs to use crowdsensing technology for city sensing and data collection. As a response, in the face of increasingly complex sensing tasks, crowdsensing can also use DT to create a twin layer to manage the sensing system. In other words, DT can act as a platform to schedule and allocate sensing tasks.

The combination of DT and crowdsensing can achieve the precise sensing of urban conditions. Crowdsensing can provide rich urban data for the construction and verification of DT models. At the same time, DT technology can optimize the data collection process of crowdsensing through real-time data analysis and model decision-making [301]. Sensing data quality and sensing coverage can then be improved. With the combination of DT and crowdsensing, multi-source fusion and interactive visualization of urban traffic data can be achieved. In this way, it can provide more accurate and effective decision-making support for urban planning, construction, traffic management, and services. In addition, the combination of DT and crowdfunding can not only promote the intelligent development of urban transportation, but also improve the operational efficiency of the city [302]. To sum up, DT has apparent advantages in the field of crowdsensing, which is worth exploring by researchers in the future.

3) Metaverse: Metaverse is commonly referred to as a network of interconnected 3D virtual worlds, which is described as the "Internet of virtual reality" [303]. In reality, Metaverse is a platform that facilitates the creation and hosting of various digital sub-worlds. It further blurs the lines between the physical and virtual realms. Metaverse mainly includes two roles, virtual service provider and user. Each virtual sub-world within the Metaverse system is operated by a virtual service provider and offers a unique set of virtual services to platform users. The development of Metaverse involves multiple fields, such as virtual reality, blockchain, AI and other fields [304]. It also plays an important role in the construction of smart cities.

Despite its huge potential benefits, the Metaverse is still in the early stages of development. One of the challenges facing the Metaverse is how to replicate the real world in its virtual environment effectively. Synchronizing DT is one solution to this challenge. By utilizing DT technology, users can interact with virtual representations of physical entities in a way that simulates real-world interactions. This also allows virtual service providers to develop new business models and services based on DT technology. The solution proposed by Han *et al.* in [305] is a dynamic hierarchical framework for synchronizing the Metaverse with IoT devices. This framework can collectively sense the current state of physical entities, represented by DTs of virtual service providers utilizing mobile IoT devices.

Since the Metaverse needs to collect relevant information from the physical world to synchronize in the virtual world, efficient data collection methods are required to synchronize this process. Crowdsensing, as an efficient distributed data collection method, can be used to integrate with the Metaverse. Here, utilizing crowdsensing will be a novel IoT-assisted synchronous data collection framework, in which physical object state data can be collected by various movable IoT devices. Wang *et al.* in [306] innovatively proposed a metaverse modeling data collection framework based on crowdsensing, which is both timely and safe. A five-layer architecture is proposed to enable the Metaverse server to employ staff to collect environmental parameters and user information. Each layer in the proposed five-layer architecture is responsible for data calculation and encryption, which facilitates the efficient and secure transmission of data within the Metaverse. This provides direction for the combined development of crowdsensing and the Metaverse, with great potential to receive significant attention in future.

4) AI-Generated Content: Recently, AI-Generated Content (AIGC) has emerged as a new approach to data production, manipulation, and modification [307]. AIGC services are based on large-scale pre-trained models with billions of parameters, with the aim of enhancing social production efficiency and saving labour costs. The powerful computing power of cloud data centres can be used to train AIGC pre-trained models, such as GPT-3 for ChatGPT and GPT-4 for ChatGPT Plus. AIGC is expected to provide a large amount of synthetic data for smart cities, providing tremendous productivity and economic value to society.

Data collection is an integral part of AIGC [308]. It plays an important role in defining the quality and variety of materials created by AI systems. The data used to train an AI model affects the patterns and relationships learned by the AI model, as well as the output. It is obvious that crowdsensing is a widely used data collection technique [309]. Through crowdsensing, data can be collected from various entities in smart cities, including individuals, MDs, vehicles, and more. The collected data can be used to train ML models to generate text and images, among other applications [310]. A common example is Amazon Mechanical Turk. By paying individuals to perform tasks such as annotating text or images, these tasks can then be used to train AIGC models.

In addition, sensing entities in smart cities can also be equipped with AIGC services. For example, vehicles and UAVs can be used as heterogeneous base stations to enhance the coverage of mobile AIGC networks, providing AIGC models and content to users anytime and anywhere [311]. Mobile AIGC networks utilise a collaborative computing framework in the cloud to deliver AIGC services, while also requiring large amounts of heterogeneous data and computing power. Edge computing enables users to access high-quality AIGC services with lower latency [312]. Combined with edge computing, UAVs can act as aerial wireless base stations, edge computing servers, and edge cache providers in mobile AIGC networks [313].

Overall, crowdsensing can provide an important data source for AIGC services and reduce service costs. Various sensing entities in smart cities also play a pivotal role in the mobile AIGC network. Therefore, AIGC can better serve the construction of smart cities.

VII. Conclusion

In this survey, we provided a systematic review of the recent research and development of crowdsensing in smart cities. At first, we introduced the background of crowdsensing, past review studies, sensing entities, application scenarios, and related technologies. Subsequently, we comprehensively summarized and classified the research on crowdsensing in recent years. Specifically, we categorized studies according to different sensing entities in smart cities. The architecture, research problems, solutions, and application scenarios for each field are discussed in detail. In particular, we also performed an analysis of the UAV-assisted sensing scenario. Then, we described the crowdsensing-related platforms, simulators, and applied datasets. Finally, we discussed the research fields related to crowdsensing and the possible future research directions.

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