A Survey of Incentive Mechanisms for Participatory Sensing

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***Abstract*—Participatory sensing is now becoming more popular and has shown its great potential in various applications. It was originally proposed to recruit ordinary citizens to collect and share massive amounts of sensory data using their portable smart devices. By attracting participants and paying rewards as a return, incentive mechanisms play an important role to guarantee a stable scale of participants and to improve the accuracy/coverage/timeliness of the sensing results. Along this direction, a considerable amount of research activities have been conducted recently, ranging from experimental studies to theoretical solutions and practical applications, aiming at providing more comprehensive incentive procedures and/or protecting benefits of different system stakeholders. To this end, this paper surveys the literature over the period of 2004–2014 from the state of the art of theoretical frameworks, applications and system implementations, and experimental studies of the incentive strategies used in participatory sensing by providing up-to-date research in the literature. We also point out future directions of incentive strategies used in participatory sensing.**

***Index Terms*—Participatory sensing, incentive schemes, survey.**

I. Introduction

SMART devices, including smartphones, iPad, and tablets, etc., are used not only as a means of communication mobile devices of choice, but also as powerful sensing units with a rich set of embedded sensors, such as accelerometer, digital compass, gyroscope, GPS, microphone, camera, etc. Collectively, these sensors are enabling a new type of applications that can recruit ordinary citizens to collect and share sensory data, and ultimately give rise to a new area of research, called "participatory sensing" [1]. By using these embedded sensors, the ordinary citizens act as "participants" to sense multi-dimensional data streams from the surrounding environment and share these streams using existing communication infrastructure [2]. Participatory sensing has shown its great potential in retrieving context-aware information across a wide variety of application domains, such as healthcare, social networks, safety, environmental monitoring and transportation, for academia, industry and government agencies. For example, Yang *et al.* proposed an indoor localization scheme for participatory sensing based systems, where any participants could upload their location information to the server, and other participants who were in the same place could download this information for indoor positioning [3]. Massung *et al.* used a participatory sensing system to support pro-environmental community activism, where they implemented an application to make participants undertake lightweight environmental data collection jobs [4]. Mason *et al.* designed a system to allow wild exploring participants to upload tiger photos with GPS information in order to track wild tiger location [5].

The general system flow of a participatory sensing application is shown in Fig. 1, where there are three categories of main stakeholders, namely: (a) task publisher, (b) platform, and (c) a crowd of participants. When a certain type of sensory data is required, the task publisher publishes a corresponding sensing task with the detailed quality-of-information (QoI) requirements to the platform, such as accuracy, granularity, timeliness, and quantity, together with the amount of affordable rewards to be paid to the participants. The platform then matches each task (or subtasks if the task needs to be divided into parts, and handled by multiple groups of different participants) with suitable participants. Following some basic negotiation processes (which serves as a key part of the incentive mechanism, and is the focus of this paper), the participants reach an agreement with the platform on their expected amount of rewards. After that, they collect sensory data, and upload them to the platform.

Incentive mechanisms severing as key part of a system have also been widely implemented in many other different areas. Wang *et al.* modeled dynamics of incentive mechanisms in autonomous networks [6]; Zhao *et al.* used incentive protocol to encourage cooperation among end-nodes so as to deliver a scalable and robust service in peer-to-peer networks [7]; Huang *et al.* provided incentives for individual users of an *ad hoc* mobile network to cooperate with each other [8], etc.

Manuscript received June 16, 2014; revised November 11, 2014; accepted December 28, 2014. Date of publication January 6, 2015; date of current version May 19, 2015. This work was supported in part by the National Natural Science Foundation of China under Grants 61370197, 61300179, and 61271041 and in part by the Doctorate Fund Projects of China under Grant 20130005110011. *(Corresponding author: Chi Harold Liu.)*

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Digital Object Identifier 10.1109/COMST.2014.2387836

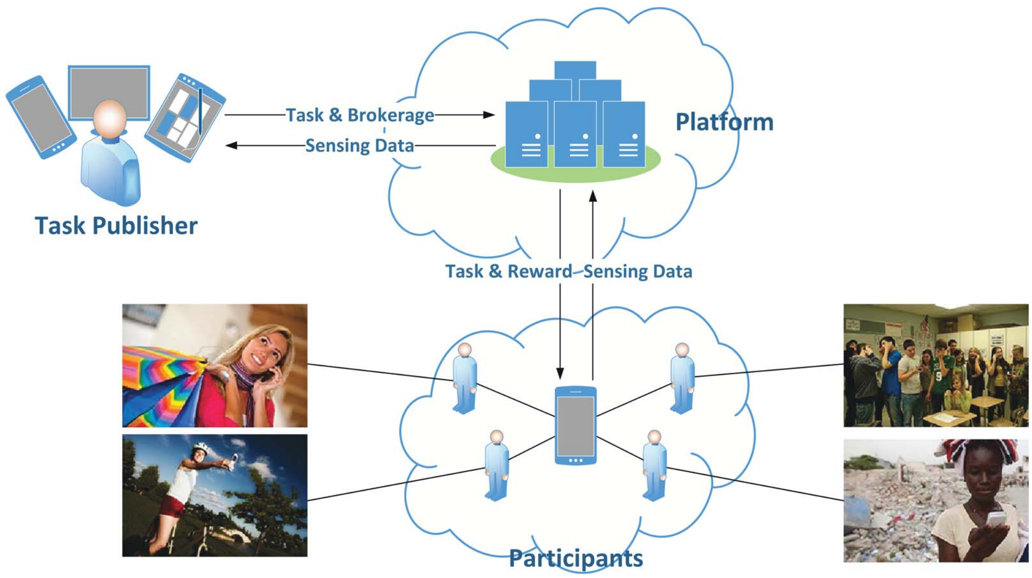

Fig. 1. The general system flow of participatory sensing, where task publishers publish sensing tasks through the platform to participants. Participants collect sensory data, upload them to the platform, and receive rewards from task publishers through the platform.

Rewards are introduced into the participatory sensing system because: (a) participating in a crowd-sensing task may incur monetary costs, network bandwidth usage, and shortened battery life for mobile users, and thus rewards are used to offset and encourage them to tolerate these costs and make contributions; and (b) unlike traditional sensor networks where a sink node has the complete control of all sensors' behaviors, smart devices are rather personal, and only the owner can decide when, where and how to use it for participation. In this regard, rewards can be used to somehow influence their decision, and thus help improve the overall attained QoI of the collected data. Wang *et al.* argued that without proper incentives, private provisioning of public goods was always suboptimal [6]. Within a participatory sensing system, two research challenges as stated in [9], are: (a) how to recruit and retain more participants, and (b) how to evaluate their contributions. The first challenge can be understood from the participant's perspective, i.e., that the role and effectiveness of incentives for motivating people cannot fully be measured unless their needs, goals and concerns are completely understood [10]. That is, how to provide profitable, secure, and fair sensing opportunities to maintain enough participants. The second challenge is from the task publisher/platform's end, as different tasks need variable sensing duration and quality [11], and thus how to provide higher quality sensory data by offering the smallest amount of rewards is challenging.

To this end, this paper surveys the literature over the period of 2004–2014 from the state-of-the-art of theoretical frameworks, applications and system implementations, experimental studies of the incentive strategies used in participatory sensing by providing up-to-date research in the literature and future research directions. The rest of this paper is organized as follows. In Section II, we start from theoretical perspectives by comparing existing strategies based on their purposes and procedures. Second, different kinds of participatory sensing applications and implementations are presented in Section III. Third, we represent existing experimental studies for incentive strategies in Section IV. Last, we discuss the way to provide trustworthiness of sensing data in participatory sensing systems and reputation schemes in Section V. Finally, after reviewing the research challenges and discussing the open issues of these strategies, we depict our vision on future research directions in Section VI, and Section VII concludes the paper.

II. Theoretical Frameworks

In this section, we review 31 scientific publications related to the theoretical frameworks of incentive strategies for participate sensing, and discuss their generalities and differences, as summarized in Tables II–IV. In these tables, their motivation, adopted incentive model, assumptions, inputs, objectives, constraints and outputs of their constructed optimization objectives, are extensively compared. We observe that the existing theoretical frameworks can be divided into different categories from different aspects.

- Considering different purposes to employ these incentive strategies, the research in [12], [13], the user-centric method in [14]–[19], IDF method in [20], and [21]–[27] are all "user-centric" approaches that focus on how to recruit more users and improve their motivation. In contrast, the "platform-centric" method in [14], the ITF method in [20], and schemes in [28]–[41] are "platform-centric" approaches to mainly focus on how to improve the information gain of the platform and reduce the overall sensing cost.
- With regard to different incentive negotiation processes, schemes in [12], [14], [16], [28], [29], [42]–[57] are all "Price-Decision-First" approaches. That is, the reward each participant will receive is decided before the sensory data are uploaded, thus giving participants a choice as whether or not to accept the incentive offer. In contrast, schemes in [19], [20], [30], [31] are all "Data-Upload-First" approaches, i.e., sensory data upload is done before incentive decisions.

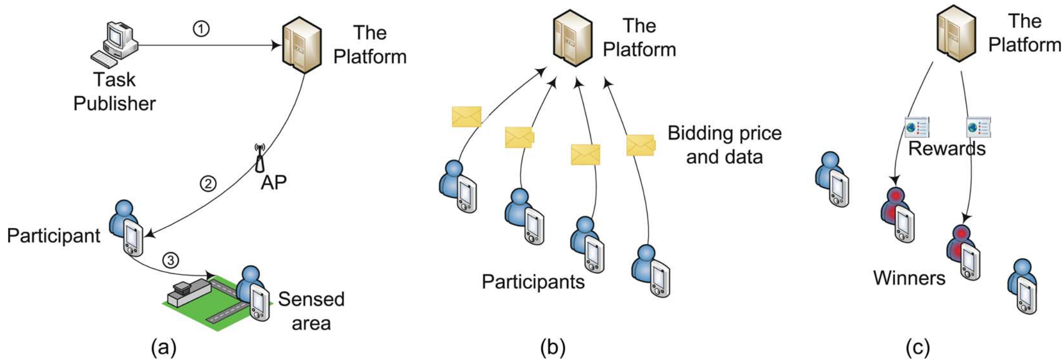

Fig. 2. The work flow of Reverse Auction based Dynamic Price, where (a) was data sensed phase, (b) was price bad phase and (c) was participants selected phase [12].

A. *Different Optimization Goals*

As stated above, considering different design goals, existing incentive strategies can be divided into two categories: (a) user-centric approaches focusing on how to recruit more users and improve their motivation, and (b) platform-centric approaches focusing on how to improve the information gain of the platform and reduce the overall sensing costs.

1) User-Centric Approaches: Lee *et al.* introduced a reversed-auction based incentive mechanism, called "RADP," where participants sent their incentive expectations to the platform, and those with lowest expectations were chosen as auction winners to carry on the sensing task [12]. The proposed work flow was shown in Fig. 2, where task publisher first sent the requirement to the platform, and then the platform either sent the task to participants, or participants chose the task from the platform [see Fig. 2(a)]. After, the participants bade for selling their sensing data [see Fig. 2(b)]. Finally, the platform selected the predefined number of participants with lower bidding prices, and they received their bidding prices for their sensing data as a reward, as shown in Fig. 2(c).

One drawback of using RADP is that participants who contribute higher quality sensing data but cost more energy and time may become starved frequently, because their bidding prices are beyond the selection threshold. Therefore, these users may stop participating the future tasks. To overcome this problem, Lee *et al.* proposed a strategy where virtual credit was given to those participants who lost in the previous reverse auction a specific reward only for their participation [13]. The only purpose of using this virtual participant credit (VPC) was to maintain adequate number of participants by keeping price competition and preventing them from dropping out of RADP. When a participant i with VPC v_i proposed his/her bidding price o_i to the platform, the previous would cut down his/her bidding price to $(o_i - v_i)$ which made his/her price cheaper, and thus increased his/her winning probability. When he/she won, what he/she could earn was o_i and his/her v_i would become to 0. The authors called this "RADP-VPC" system. However, in the proposed strategy, a participant could set an extremely high bid price, and thus he/she would ultimately be paid this high price by participating only once, which was not fair for those participants with long-term relatively low bidding prices.

The user-centric method proposed in [14], called "MSensing," extended RADP by introducing a better auction model for the platform to guarantee participants' benefits. The authors proved that the basic reversed auction model failed to guarantee the profits of auction winners whose price claims were truthfully their sensing costs. Then, MSensing was proposed to solve the problem by giving auction winners the highest bidding price that could win the auction, instead of their own bidding prices. However, as shown in Table II, MSensing specifically required the task publisher to set the value of each piece of required data as *a prior*, which might not be feasible for wide area data collection, where the required data value of each sub-area could vary significantly.

RADP and other auction based incentive mechanisms were named "winner-take-all" in [15]. That was, the platform was only interested in the best quality data with lowest price. The winning participant took the entire prize and losers wasted their energy but earned nothing. Thus the authors proposed a mechanism named "Top-K Rule," to have participants participate in a pre-qualification stage. This stage filtered participants based on the idealized production qualities they could produce, and then it ran a contest with only those participants deemed to provide high production qualities. In the beginning, each participant i submitted a bidding pair (θ_i, E_i) indicating its expertise type θ_i and the amount of effort E_i it could devote during the contest. Here, $\alpha_i(= E_i\theta_i)$ denoted the ranked idealized quality, which could also be viewed as participant i's cost. Bidders with top-K qualities were selected for the contest. The selected participants paid an entry fee for participation, and then they used their data for bidding and the platform selected the winner and rewarded him/her.

Another extension came from [16], which guided participants to figure out their most profitable bidding prices and participating levels, e.g., by submitting different numbers of data samples or different types of data. The proposed strategy involved a Bayesian game [58] in the phase of a participant's bidding price decision, with the costs of his/her competitors as inputs. Table II illustrated the details. Although its nature conformed to the market economy law of supply and demand, knowing other participants' cost was unlikely to be possible when all participants were moving around and one's competitors were always changing.

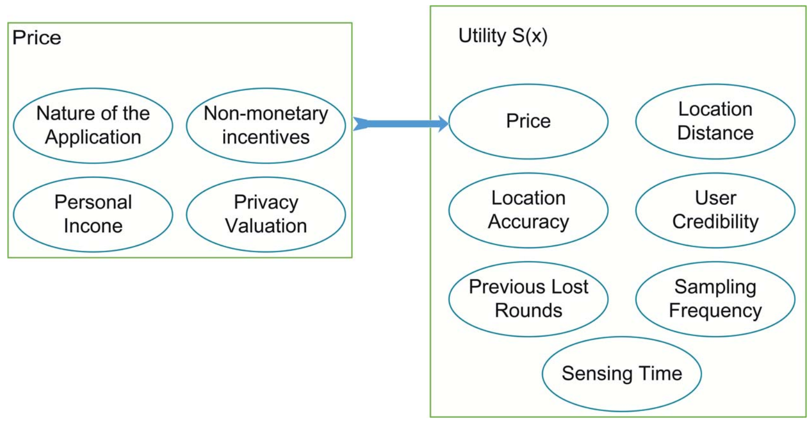

Fig. 3. Attributes affecting the utility function, where price was not the only decision element [18].

Duan *et al.* explored a user-centric incentive scheme, where a task publisher published a task successfully, only if it could recruit enough participants under budget constraint [17]. They proposed an incentive mechanism for two types of applications, namely: data acquisition (DA) and distributed computing (DC) applications. The authors argued that the platform could attract enough participants under a minimum reward, if it knew the cost of them; also, the participants could earn more, if they sold their privacy information to the platform.

Krontiris *et al.* argued that the traditional reverse auction did not consider that sensing data was actually of different qualities [18]. Therefore, it was unfair for participants when the platform only considered their bidding prices but fully ignored the data quality. The authors then proposed a multi-attributive auction (MAA) that considered many attributes (see Fig. 3 for details) of the sensing data, to help the platform select the highest quality data and give participants the incentive through price negotiation. A utility function was also proposed where each relevant attribute could be valued and what participants bade was not only its own price, but also the weighted sum of all these considered data attributes, as:

$$S(x) = \sum_{i=1}^{n} w_i S(x_i), \tag{1}$$

where $\sum_{i=1}^{n} w_i = 1$, w_i is the weight factor, n is the number of relevant attributes decided by the system operator, and $S(x_i)$ denotes each valued attribute. The larger $S(x)$ is, the more chance the participant would be selected.

Lv *et al.* mainly focused on how to encourage existing participants to recruit more participants in [19]. In their proposal, the obtained incentive was both decided by the contribution of his/her uploaded data, and the contribution of those participants he/she managed to solicit. The insight was to give more rewards to those who had solicited more participants, by taking away rewards that ought to be given to those who failed to solicit enough participants. This strategy was helpful to recruit new participants. However, the payment to later-recruited participants might be insufficient to cover their sensing costs, and thus they might leave the future tasks.

Lou *et al.* proposed the IDF method which first studied the fairness of incentive distributions among participants in a specific scenario, where data contributors were also data consumers [20]. The fairness was reflected on the relationship between each participant's data contribution and his/her received service quota for future data consumptions. As shown in Table II, an optimization problem was formulated to achieve the maximum fairness, measured by the Jain's index [59] for all participants. However, this work did not further explore how to most fairly evaluated the data contribution of all participants.

An auction scheme was designed by [60] and [61], where their proposed process was that the platform rejected the first batch of bidders and used their samples to weight the quality of the rest of bidders' data. Zhang *et al.* called this auction scheme, as "Threshold-based Auction (TBA)" [21]. In it, the first batch of participants was used to compute a price threshold, and then other participants whose price was lower than this threshold would be chosen. Although TBA maximized the platform' utility, it had a shortcoming that the first batch of bidders had no chance to be selected. Thus, the authors further designed a Truthful Online Incentive Mechanism (TOIM), and a Truthful Online incentives Mechanism for arrival-departure (TOIM-AD). Different from TBA, these two mechanisms took the first batch of participants into considerations. After computing the price threshold, they selected participants from the first patch to the last one. The difference between TOIM and TOIM-AD was that TOIM-AD considered the participants who had won the bidding but did not leave the task. Therefore, the platform would reject these participants before every bidding began.

Similar to [21], Zhao *et al.* overcame the shortcoming of [60], [61] that hurt the participants' motivation [22]. They proposed a multi-stage sampling-accepting process which divided a task into some small ones. In every small task, participants could be rewarded based on their bidding prices and data quality. The latter small tasks could weight data quality by using the samples of the former one. Compared with [21], the authors in this paper also divided a task into small ones but with different long time slices and different amount of affordable task budget. In a new time slice, a new price threshold would be computed based on the price of former time slice.

Zhang *et al.* proposed a reputation-based incentive mechanism, where a participant with high reputation could always receive services from others upon requests, while participants

TABLE I
DIFFERENT FAIRNESS USAGE

Purpose	Features	Reference
gave a participant a chance	auction losers have a chance to be selected	[13]
	the first batch of auction participants has a chance to be selected	[21]
	the first batch of auction participants has a chance to be selected	[22]
gave a participant a fair reward	weighted data quality from different attributions	[18]
	made sure of that a participant's contribution level and his/her demand was equal.	[20]

with low reputations got served only when he/she requested services from others [23]. In this paper, a threshold H was introduced to define high reputation and low reputation, and a "social rule" was defined based on H to calculate their reputation scores. A participant acted both as a platform (sending information) and a publisher (requesting information), but here the platform did not have any utility at all. More details about employing reputation schemes in participatory sensing, and incentives in particular will be discussed in Section V.

In order to use incentive schemes to attract more participants, Cheng *et al.* widened the scope of incentives from device/user level to the group level [24]. That was, participants were organized into a team to do a sensing task and share incentive rewards. No matter who finished the task, what he/she earned as rewards could be consumed by others in the same group. Since the sensing data was collected by a team of participants, the amount of credits actually belonged to the whole team, but not the individual user.

Tsujimori *et al.* argued that sometimes participants could not sense data of the exact place, or point of interest (POI) [25]. To overcome this problem, they proposed three thresholds, distance threshold, time threshold and reward threshold. The values of these three thresholds were all set by the platform. If the distance between a participant's sensing position and POI was not longer than the distance threshold, the participant used a longer sensing time than the time threshold, and more rewards were given than the reward threshold. In this way, this piece of sensing data was available. Therefore, how much a participant would be rewarded highly depended on the sensing time, i.e., the longer the sensing time was, the more reward he/she could earn, but between a maximum/minimum bound.

Wang *et al.* optimized SenseUtil [62] where a distance threshold was introduced, i.e., only the participant whose distance from the POI was shorter than the threshold could take the sensing task [26]. This method could avoid unnecessary energy and bandwidth consumption on both the platform and participant sides.

To maintain as many participants as possible, Sun *et al.* proposed an incentive scheme to stimulate participants to cooperate in participatory sensing systems [27]. That was, even a participant was not selected, he/she still had chance to be rewarded. The platform decided whether subsidies were distributed or not, according to his/her cooperation behavior at the end of a sensing period where the system divided the entire sensing time into small intervals. The authors proposed the concept of "social state" for the participant to decide whether he/she had participated in sensing data. They also proposed a concept of "whittle indexability" [63] to quantify this social state. After every time a piece of sensing data was uploaded, the platform would update the participants' social state table.

From the above analysis, we observe that a few types of different methods to implement "user-centric" approaches. One is to integrate the fairness aspect thought into the designed incentive mechanism to improve participants' motivation. In this regard, we have surveyed five fairness related papers as shown in Section II-A1. As shown in Table I, consider different purposes, these research outputs can be divided into two categories: (a) fairness is employed in incentive mechanisms in order to provide participants an opportunity to be selected; and (b) fairness is employed in incentive mechanisms in order to provide them a fair reward. Compared with RADP that rejected the participant who asked a high reward [12], participants in RADP-VPC incentive systems had a chance to be selected [13]. Similar to the auction scheme designed by [60] and [61] rejected the first batch of bidders who did not have a chance to be paid, Zhang *et al.* in [21] and Zhao *et al.* in [22] proposed their own solutions to consider these first batch of bidders to overcome this unfairness problem. The work of Krontiris *et al.* and Luo *et al.* aimed to give a participant a fair reward, which meant that what a participant could gain was equal to what he/she has been paid. Specifically, Krontiris *et al.* proposed MAA that weighted sensing data quality from different attributions, such as sensing time, location accuracy, sampling frequency, etc., to make sure that the participant in this system could be given a fair reward [18]. Lou *et al.* proposed that a participant's contribution level was equal to his/her demand in a participatory sensing system [20].

2) Platform-Centric Approaches: GBMC [28] and ISAM [29] extended RADP from the aspect of using different optimization objective functions, aiming to achieve most accurate sensing result. Specifically, the goal of RADP was to achieve maximum data amount, while GBMC aimed to achieve maximum coverage and thus improve the quality of sensing results, and ISAM aimed to achieve maximum information gain, or minimum error between the exact average and the average estimated from samplings, as:

$$\begin{aligned} &\text{RADP}: \ \max 1/c_i, \\ &\text{GBMC}: \ \max W_i'/c_i, \\ &\text{ISAM}: \ \max d_i/c_i = \min E\left(y_i' - y_i\right)^2/c_i, \end{aligned} \tag{2}$$

where d_i, c_i denote the contributed data and required payment of each user i, W_i' is the sensing coverage gain of i, and y_i', y_i are the estimated average and the exact average, respectively. Compared with RADP, GBMC and ISAM not only purchased data from the lowest seller, but also considered their spatial distribution. The idea of using incentive strategy to satisfy the coverage requirement is also studied in [64].

TABLE II
COMPARISON OF DIFFERENT INCENTIVE STRATEGIES FOR PARTICIPATORY SENSING (PART 1)

Reference	Motivation	Incentive model	Incentive Solution				
			Assumption	Input	Objective	Constraints	Output
RADP [12]	minimized cost without user dropping out	Reversed auction	Participants had different costs	bid price of each user	minimized server's cost	total budget constraints	auction winners
RADP-VPC [13]	minimized cost without user dropping out	Reversed auction with virtual participant credit	Participants might drop out if they were not selected	bid price of each user	minimized server's cost and gain quality data	total budget constraints	auction winners
User-centric [14]	user had more control over their payment	Reversed Auction	the value of each task was known	bid price of each user	the reasonable price offer	Payments less than tasks values	auction winners and payments
Platform-centric [14]	maximized platform utility	Stackelberg Game	the costs of each participants were known	cost of each user	maximized platform utility	N.A.	the platform's total reward
Top-K Rule [15]	minimized non-winning participants' cost	Auction	N.A.	participants' expertise type and effort amount	selected participants and obtained quality data	N.A.	selected participants and auction winner
Optimal incentive [16]	user's participation level determination and maximized platform utility	Reversed Auction and Bayesian game	the cost of each user was a continuous random variable by choosing different participation levels	each user knew probabilistic information about costs of others	minimized total cost of compensating participants	maintaining service quality	auction winners and each user's participation level
DA [17]	collect enough data	Stackelberg Game	participants were homogeneous in contribution and efficiency	total numbers of participants and reward	the reasonable price offer	total budget constraints	number of participants
DC [17]	solved complex scientific computing problems under budget constraint	Stackelberg Game	participants were homogeneous in computing efficiency	each type of task and reward	the reasonable price offer	total budget constraints	number of participants
MAA [18]	participants had quality sensing data can be chosen	auction	real-time services were provided	utility function scores	gained high quality data	budget constraint	auction winners
Incentive tree mechanism [19]	evaluated user's contribution taking into account the participants he solicited	Data-Upload-First	participants could recruit new participants	participants contribution and solicitation tree	N.A.	total incentives were fixed	incentive for each participants
IDF [20]	evaluated user's contribution for maximizing fairness	Greedy	users were both data producers and data consumers	each user's contribution and consumption of each time slots	maximized weighted fairness of all users	N.A.	service quota of each user for the next round

Yang *et al.* proposed a platform-centric model for the task publisher to plan his/her most profitable incentive budget [14]. The incentive negotiation procedure was modeled as a Stackelberg game [65]. In it, the platform was the leader and decided payment to each participant, while the participants could only tailor their actions to the platform. All participants were assumed to be absolutely rational, and could dynamically adjust their bidding prices according to the given incentive budget and costs of other participants to maximize their profits. However, this model required heavy computational procedures on participants' resource-constrained smart devices, and it also required that the platform knew the actual sensing cost of all participants, as summarized in Table II.

Lou *et al.* proposed an ITF method, aiming at maximizing the total amount of data collection and their quality [20]. In their proposal, a participant's sensing data was uploaded without an explicit incentive negotiation phase, thus giving the platform more privilege to allocate user payment. The platform encouraged participants to provide more sensing data by introducing a more competitive incentive distribution strategy. That was, extra rewards were given to participants with more contributions. However, similar to [19], the payment to some participants could be insufficient to prevent them from continuing to participate in future tasks.

"Peer Truth Serum" approaches in [30] and [31] both considered the trustworthiness of participants' uploaded data. They assumed that some collected data may be untruthful, and it used the truthful data from each participant to evaluate its improvement to the overall measurement accuracy, without explicitly knowing the accuracy of each user's data. Then, this contribution was used to decide their incentive payment from a limited budget. Later, Zhang *et al.* in their paper first formulated this exchange procedure as a two-side market, where task publishers and participants were matched by the platform and played gift-giving games repeatedly [31]. Task publishers paid a participant according to his/her historical reputation, and updated their reputation after this task. The idea was that, a participant with high reputation could provide high quality sensing data for task publishers, and thus they would receive more rewards. Along this line, in [31], an optimal and sustainable strategy was also proposed, to achieve the highest social welfare for the platform. We specifically mention this paper simply because it clearly separated participants from the central platform, which were tightly coupled in most other papers.

A consensus prediction payment rule for truthful reporting was proposed in [32]. The consensus task was that it had a correct answer and many participants were able to share assessments about this correct answer. This payment rule rewarded a participant based on how well his/her report could predict the consensus of other participants. That was, if a participant's report was much different from others', he/she was considered not sending truthful report and in turn would receive low incentive payment. A Bayesian-Nash equilibrium [66] was used to implement the consensus prediction payment rule. Let β_i: $\Sigma_{-i} \rightarrow \Sigma_i$ denotes player i's best-reply correspondence in terms of strategies:

$$\beta_i(\sigma_{-i}) = \{\sigma_i \in \Sigma_i |\ \forall t_i \in T-i : \sigma_i(t_i) \in \varphi_i(t_i; \sigma_{-i})\}, \quad (3)$$

where N denotes the set of players, i denotes a player, T_i denotes the set of types of player i, t_i denotes a type of player i, Σ_i denotes the set of strategies for player i, $\Sigma := \prod_{i \in N} \Sigma_i$ denotes the set of strategy profiles, σ denotes a strategy profile,

TABLE III
COMPARISON OF DIFFERENT INCENTIVE STRATEGIES FOR PARTICIPATORY SENSING (PART 2)

Reference	Motivation	Incentive model	Incentive Solution				
			Assumption	Input	Objective	Constraints	Output
ITF [20]	evaluated user's contribution for maximizing social welfare	Iterative Tank Filling	users were both data producers and data consumers	each user's contribution and consumption of each time slots	maximized aggregate user's utility	services quota added up to total contribution	service quota of each user for the next round
TOIM and TOIM-AD [21]	kept participants' motivation and evaluate their data quality	Auction	N.A.	participants data and price	the reasonable price offer	total budget constraints and recruited numbers	participants' incentive
User-centric [22]	kept participants' motivation and evaluate their data quality	Auction	N.A.	participants data and price	the reasonable price offer	total budget constraints	participants' incentive
User-centric [23]	kept participants exchanging information	game theory Nash equilibrium	service exchange was socially valuable	participants' data	requester gained informaiton	participants' history repuatation	participants' reputation
User-centric [24]	attracted more participants	N.A.	N.A.	group's data	maximized group's common expected utility	N.A.	group's credits
SenseUtil [25]	maximized sensing activities and maintaining reasonable sensing cost	N.A.	N.A.	participant's data	N.A.	time, reward and distance thresholds˙	participant's rewards
SenseUtil [26]	maximized sensing activities and maintaining reasonable sensing cost	N.A.	N.A.	participant's data	N.A.	time, reward and distance thresholds˙	participant's rewards
User-centric [27]	maintained participants as many as possible	Date-Upload-First	N.A.	participants who wanted to participate	N.A.	cost constraint.	participants who were chosen
GBMC [28]	maximized coverage	Reversed auction	user's coverage was different	bid price, coverage, location of each user	maximized coverage	total budget constraints	auction winners
ISAM [29]	maximized information quality	Budget Feasible Mechanisms	qualities of information of users were different	quality of information and cost of each user	maximized information quality	total budget constraints	auction winners
Peer Truth Serum [30]	evaluated user's contribution for encouraging accuracy and truthfulness	Data-Upload-First	users' data contribution were not always accurate.	uploaded data of participants	N.A.	N.A.	incentive for participants

TABLE IV
COMPARISON OF DIFFERENT INCENTIVE STRATEGIES FOR PARTICIPATORY SENSING (PART 3)

Reference	Motivation	Incentive model	Incentive Solution				
			Assumption	Input	Objective	Constraints	Output
repeated game protocol [31]	calculated user's payment according to his reputation	Data-Upload-First	users participated in tasks repeatedly	participants' reputation	N.A.	N.A.	participants' incentive
CPR [32]	evaluated user's contribution for encouraging accuracy and truthfulness	Data-Upload-First and Bayesian-Nash equilibrium	participants' reportings were not always truthful.	uploaded data of participants	N.A.	N.A.	incentive for participants
Platform-centric [33]	maximized service provider's profit	Bayesian game and all-pay auction	the higher contribution the better	uploaded data of participants	maximized service provider's profit and satisfy participants	N.A.	participants' incentive
Platform-centric [34]	maximized service provider's profit	game theory and greedy algorithm	participants were selfish	uploaded data of participants	the platform received data more probability	participant first delivered data could be rewarded	participants' incentive
Platform-centric [35]	improved the data gain	greedy algorithm	participants could relay one data at a time	uploaded data of participants	the platform received data more probability	data freshness	participants' incentive
TM-Uniform [36]	maximized requester's and participants' utility	uniform payment	participants did one task and a task was done once	participants' cost	minimised cost	budget constraint and participants' skills	recruited participants and payment for them
Pick-A-Crowd [37]	selected specific participants to specific tasks	uniform payment	participants were more competent at tackling tasks related to their categories	budget and participants' profiles	participants' reward	budget constraint and participants' profiles	recruited participants and payment for them
Platform-centric [38]	executed business processes in a cost-optimal way	Price-Decision-First	task basic information would be published in platform	task estimation information	fulfilled process deadline and minimized rewards	task deadline	task reward, etc, information
Platform-centric [39]	minimized cost and gained high quality sensing data	game theory	participants take unpaid training willingly	sensing data	satisfied requester's quality requirement	budget constraint	task reward
Platform-centric [40]	chose the efficiently incentive mechanism	data-upload first	participants took unpaid training willingly	sensing data	gained high quality data or low cost	budget constraint	task reward
Platform-centric [41]	attained coverage without scale	games and social applications	participants liked mobile games or social applications	N.A.	attained coverage without scale	N.A.	N.A.

σ_i denotes a strategy profile of i, $\varphi_i(t_i;\sigma_{-i})$ denotes the set of actions for i that maximized payoff, σ_{-i} denotes the strategy profile of the other players except i, a strategy profile $\sigma \in \Sigma$, $\forall\, i \in N$ and $t_i \in T_i$, $\sigma_i(t_i) \in \varphi_i(t_i;\sigma_{-i})$.

Luo *et al.* aimed at maximizing the received contribution and profit for the platform [33]. They designed an incentive scheme to reward participants who made the highest contribution. They argued that since all participants contributed their data, and thus all of them should be paid some monetary reward as incentives to offset their sensing cost, and kept them contributing in future tasks. The authors called this scheme as the "all-pay auction" scheme.

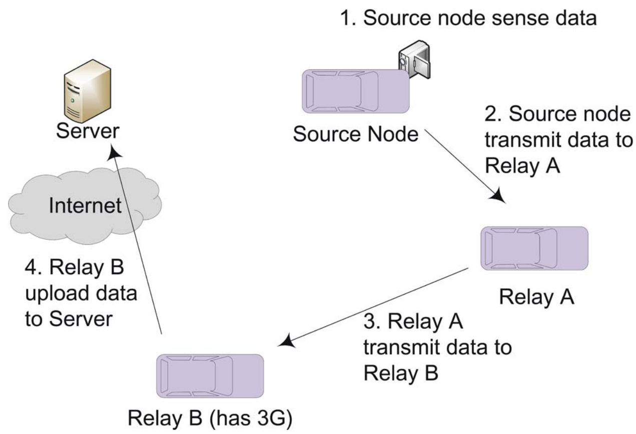

Fig. 4. The scenario of relaying work flow proposed in [35].

Low power radio technologies (e.g., Bluetooth [67], ZigBee [68], etc.) were used to deliver sensing data [34]. Before the data was uploaded, they introduced a "bargaining" procedure. Suppose participants i and j were selfish and wanted to earn more rewards, based on the probability of delivering the data to the platform successfully, i and j weighted all of his/her data each other and exchanged the data lists to understand what data i did not have but j had. With each other's list, participants i and j exchanged their equal weight data from high to low by using a greedy algorithm. After exchanging, the expected credit reward $R_i(r)$, was used by participant i to anticipate the reward of trading message type r with j, and was calculated as:

$$R_k(r) = A_k(r) \times P_k(r) \quad i, j \in k, \tag{4}$$

where $A_k(r)$ denotes participant k's message appraisal and indicated the probability that only he/she can deliver this message to the platform. The initial message appraisal is set to 1. $P_k(r)$ denotes the probability of participant k to first meet the platform.

Similar to [34], Chou *et al.* focused on the how to guarantee the successful delivery (see Fig. 4) of the sensing data to the platform [35]. But different from [34] where participants could exchange more than one piece, the authors in this paper proposed that every participant only could deliver one piece of data at a time. Therefore, in order to help participants choosing which piece of data to deliver, they designed a greed algorithm where a relaying participant would choose the most credits data to relay. As shown in Fig. 4, the source node will earn $C * \xi$, the relay A will earn $C * (1 - \xi) * \xi$, and the relay B will earn $C * (1 - \xi) * (1 - \xi)$, where C denotes the amount of credits and $\xi \in [0, 1]$ denotes a fixed commission rate. The platform will then update participant A and B's incentive accounts after it receives their uploaded data.

Goel *et al.* designed a mechanism called "TM-Uniform," based on budget constraint and certain personal skill requirement [36]. When a task publisher published a task requiring certain skills, TM-Uniform assigned it only to those participants who had the needed expertise, while ensuring budget feasibility and achieving near-optimal utility for the publisher. In their proposal, a bipartite graph $G(P, T)$ was used, where P was a pool of participants and T was a set of heterogeneous tasks. The edge $e = (p, t)$ indicated that a participant $p \in P$ could do task $t \in T$. The participants' rewards depended on the utility u of a task (u denoted a requester paid for a task, such as money, etc.), their sensing cost c_p, and requester achievement u_t (what a requester could gain, such as quality of sensing data, etc.). Every task in this mechanism had different payments. The proposed mechanism could assign the task, that had the highest payment among all available tasks, to a participant.

Similar to [36], Difallah *et al.* also proposed a scheme where a specific task should be done by only *skilled* participants [37]. Both works send tasks to participants directly, and they recorded participants' interests and skills. Different from [36], [37] proposed an incentive approach based on to what degree the participants matched the specific task, computed as:

$$r(h_i, w_j) = \frac{B * M(w_j, h_i)}{\sum_{k,l} M(w_k, h_l)}, \tag{5}$$

where $j \in k$, $i \in l$. $h_i = \{t_i, d_i, A_i, C_i\}$. t_i denotes the textual description, e.g., the task instruction provided to the participants; d_i denotes a data field that is used to provide the context for the task to the user, e.g., the container for an image to be labeled; and optionally, the set of candidate answers are denoted by $A_i = \{a_1, \ldots, a_n\}$, for the choice tasks (e.g., a list of music genres used to categorize a singer) and a list of target Facebook categories $C_i = \{c1, \ldots, c_n\}$ where Facebook is used to find specific participants. $w_j = \{P, T\}$ is the assigned digit indicating its ranking of the task h_i, where P is a set of participants' interests, and $T_i = \{t_1, \ldots, t_n\}$ is a set of tasks previously completed by w_i. This score is determined based on the likelihood of matching w_j to h_i. B is the budget. Thus, the goal is to define a scoring function $M(w_j, h_i)$ based on the participant profile. Compared with [36], [37] did not take participants' sensing cost into consideration.

Khazankin *et al.* aimed to recruit enough participants to finish a task before deadline with proper amount of reward in their proposal, participants could "book" a task whose assumed rewards and allotted sensing time was attractive to them [38]. The authors aimed to find a most beneficial trade-off between rewards, expected booking times, and allotted sensing time for a task. Although the expenses could be reduced by setting lower rewards, if the reward was too small, a task might not be booked for a long period of time, and gradually it was less likely that a participant decided to take an urgent task for a regular reward. Toward this end, they argued that rewards should be considered not only as the usual "market prices" of the respective tasks, but also sometimes could be increased to strengthen the competition among participants and shorten the booking time.

Gao *et al.* proposed a participant training mechanism to gain high quality sensing data by using low budget of micro-tasks [39]. If a participant was sending acceptable data, he/she would be rewarded, but if low quality sensing data was received, he/she would be assigned to train tasks in the "training state." Participants in training state should pass the evaluation first before they could enter the "working state" to earn reward. The task publisher maintained certain criteria on whether or not a sensing data should be accepted. When a new participant came, the task publisher could also decide whether he/she started at training or working state, and how many of them were in the training state. A game theory was employed in their proposal, where the quality of sensing data would affect not only a participant's immediate utility, but also his/her future utility. Therefore, the authors assumed that participants were happy to take some training.

Different from all the above solutions, Scekic *et al.* focused on offering system designer a methodology to select the *right* incentive mechanism [40]. As the model and simulation parameters could be changed dynamically, it allowed quick testing of different incentive setups and behavioral responses at a low cost. If an incentive mechanism was chosen, it could be deployed on the used participatory sensing system. To choose an efficient incentive mechanism, both the participants and publisher should be taken into consideration. From the participants' side, the authors proposed to consider the participant's personal characteristics (e.g., accuracy, speed, experience), authority's perception of the participant's past interactions with the system, and the set of the participant's promised rewards or punishments. From the task publisher's side, the purpose of either to achieve higher quality sensing data, or to lower the incurred sensing cost should be fully investigated.

Finally, Rula *et al.* designed an interesting approach that exerted limited control over the spatial and temporal movements of participants [41]. They used the built-in incentives of location-based gaming (such as social networking games like "Foursquare"[1] and "Gowalla"[2]) and social applications to control their movement or obtain their location information.

3) Comparison: The above analysis implies that designing a good incentive strategy is inherently closely related to how to evaluate participants' contributions, recruit enough participants in a sensing task and make the platform gain sensing data. The proposal in [12], [13], user-centric method in [14], and [15], [16], [21], [22], [28], [33] are all using auction or reverse auction to recruit more participants. But there are still some differences between them. For example, Lee *et al.* in [12] suggested that rewards should give to participants who kept participating the auction, and/or recruited new members to join the sensing task; and they further suggested that contributing more data was worth rewarding. [13], [14] and [16] extended RADP to focus on solving the problem that high price participants might not be selected fairly. Xu *et al.* in [15] and Lou *et al.* in [33] both protected participants from leaving the participatory sensing system; however their proposed methods were different. The authors in [15] proposed a participants-selected-first method in which participants would be selected before sensing data was uploaded, whereas [33] proposed "all-pay auction" in which all participants would be paid in order to keep participants in the system. [21], [22] extended the auction model in [60] and [61] to overcome the problem of using a first batch of participants' sensing data to weight the quality of the rest of bidders' data. To help the platform gain sensing data with satisfactory quality, Jaimes *et al.* in [28] suggested that participants whose contributed data could extend the coverage should be paid more. [17], [19], [24], [27] focused on recruiting more participants. [17] and [24] were group-based recruitment systems. The authors in [18], [20] evaluated the participants' contribution, and the authors in [29]–[31] focused on data trustworthiness and accuracy. Kamar *et al.* in [32] used other participants' sensing data to predict whether a particular participant's data was true or not. [34]–[37] and [39]–[41] focused on how the platform successfully received the sensing data from network communication perspectives.

On the other hand, the platform or a participant can maximize his/her own profit by knowing the sensing costs of other participants [14], [16]. Nevertheless, this may impair the profits of the majority of participants, and ultimately causes system performance degradation. Therefore, the allocated reward should not be decided by randomly generated bid prices, but by the intrinsic value of their contributed data.

In order to reasonably evaluate the "value" of a piece of contributed data, one should explicitly consider and leverage the market economy law of supply and demand. Specifically, in a considered participatory sensing system, "supply" can be the number of available participants in a specific region, and average acceptable price of all users; and "demand" can be explained as the expected gain by collecting data in an area to the overall sensing quality. Then, if we allow infinite rounds of negotiations between participants and task publisher, they should reach an equilibrium, that reveals the true value of collected data, in terms of the amount of rewards the platform should pay to each participant.

B. Different Incentive Negotiation Procedures

As mentioned earlier, considering different procedures to employ the incentive strategies, there are two categories: (a) negotiating rewards before the sensing data is uploaded, and (b) deciding rewards after the data is uploaded. Fig. 5 shows this difference.

1) Price-Decision-First: As mentioned in [12], the authors used a "fixed-price" based incentive mechanism for experiments, where the platform offered participants fixed prices for their uploaded data. The limitation was that users did not rely on the platform's real-time feedback on the achieved sensing quality to take further samples, and thus there was redundant data due to overlapping sensing area by different users. The authors also argued that some participants were willing to accept lower price offers, and thus providing fixed price to all participants was not the most efficient solution.

Based on this observation, the "auction-based" incentive strategy was also introduced in [12]. Its basic idea was that all participants sent their expectations and other relevant information, such as location and sensing capabilities (e.g., ranges), to the platform. The platform then compared all participants' expectations and sensing capabilities, and chose some auction winners to purchase their data.

The auction-based incentive method is believed to be capable of reducing the sensing cost of the platform and improving the quality of sensing results, and thus it is becoming the major category of adopted methods within the "Price-Decision-First" incentive procedure. The "user-centric" model in [14]–[16], [18], [21], [22], GBMC [28], ISAM [29] are all representative

[1]foursquare.com
[2]gowalla.com

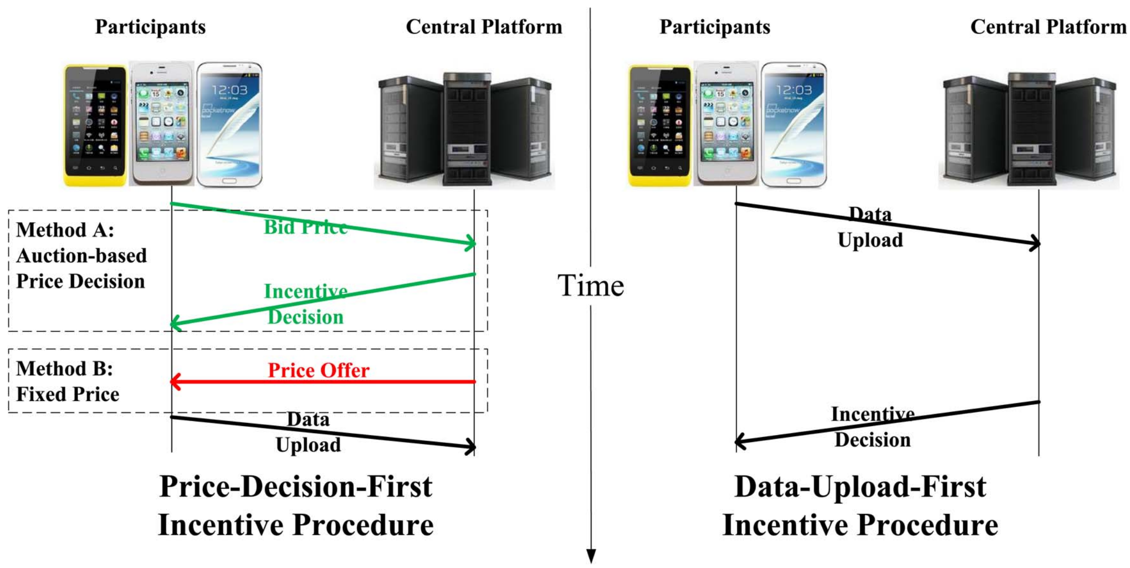

Fig. 5. Two types of incentive negotiation procedures.

examples. However, all of the auction-based methods are built on a complicated theoretical basis and further introduce communication overheads to participants' devices, and thus might cause heavy burdens for participants and inefficient use of network bandwidth. Moreover, some methods, such as RADP [12], are highly competitive to participants who have to cut down and/or keep their bidding price low enough to be selected, which may eventually result in participant's dropping out who have not been selected for long period of time. Therefore, task publishers might need to pay extra rewards to prevent participants from doing so.

2) Data-Upload-First: In the data-upload-first procedure [19], [20], [30], [31], and [49]–[57] in Section III, participants are not aware of how much incentive they will receive at the time they upload the sensory data. The platform then decides each participant's incentive rewards according to their contributions. The main difference is how these contributions are measured, as described in Section II-A in detail.

3) Comparison: From the platform's perspective, the Data-Upload-First procedure is fairer than the Price-Decision-First procedure, since each participant's contribution is measured not according to their collection cost, but the data's benefit to the sensing result. However, participants may disagree since they have spent equal cost in data sampling and uploading, but eventually receive different payment. Participants may drop out of the task due to this unfairness, which ultimately reduces the quality of data collection. Considering that the major advantage of participatory sensing systems comes from the vast number of participants collectively as a crowd, we believe that the "Price-Decision-First" incentive procedure is more suitable for general participatory sensing systems, while the "Data-Upload-First" incentive procedure can be more suitable for some specific scenarios, e.g., in [20] participants were both data contributors and consumers.

Furthermore, the auction-based approaches in the "Price-Decision-First" procedure can cause extra burdens to resource-constrained smart devices, and thus the fixed pricing can be a good alternative in practice. A possible extension is to allow the platform to provide dynamic price offers to participants in real-time according to the spatiotemporal distribution, accuracy and quantity of the supplied data.

C. Privacy-Aware Approaches

Current participatory sensing applications mainly focus on the collection of data on a large scale but forget that the sensing data possibly includes participant's private information [75]. When participants in a participatory sensing campaign contribute their data, the gathered sensory readings may reveal sensitive information of the participants to others. In addition to the spatio-temporal annotations based on WiFi, cellular network based triangulation, or similar as Sen *et al.* whose system needed participants' GPS location traces as sensing data information, the locations visited by participants could be inferred from, e.g., pictures and video clips [76]. Christin *et al.* conducted a survey with 200 anonymous participants to analyze the impact of demographics, incentives and gathering conditions on both the importance and value of privacy [77]. In their survey, the participants' average rating on the importance of privacy was 5.82 on a scale from 1 (not important) to 7 (very important). This confirms that privacy was an important issue for users. Regarding the incentives, 41% of participants would contribute their information for free, 27% expected a monetary reward, 22% would like to access additional data, and 14% of them expected additional application features. Furthermore, 18% would be interested in receiving coupons, while 6% would like to be motivated by giving a higher reputation, e.g., giving "stars" within the community. This indicates that incentive mechanisms are very important in privacy-aware participatory sensing systems. Although this survey finds out what kind of incentive participants may prefer, it may not be always the ease since using what kind of incentives also depends on the considered participatory sensing application. Applications for participatory sensing is extensively reviewed in Section III.

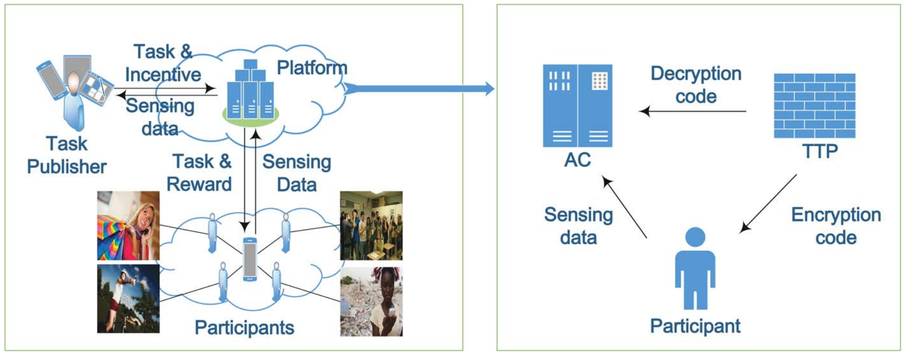

Fig. 6. The mainstream structure of privacy-aware system.

TABLE V
DIFFERENT INCENTIVE EXPERIMENTS FOR PARTICIPATORY SENSING

System encryption	Incentive deposit place	Incentive Strategy	Protection objective	Reference
one-way hash function and symmetric key algorithm	TTP	N.A.	sensing data	[69]
pseudonym and reputation transfer	AC	reputation	participant identify	[70]
pseudonym and anonymize data	TTP and AC	reputation	sensing data and participant identify	[71]
encrypted biding price and task	AC	monetary price	task and biding price	[72]
pseudonym and pseudo-credits	AC	reputation	participant identify	[73]
pseudonym	AC	reputation	participant identify	[74]

One method to preserve user privacy is to use pseudonym to replace a participant's real identity, but one have to solve a side effect: how to add new incentive scores to the right participants, since they are anonymous. Therefore, how to ensure the correctness of the employed incentive mechanism is a challenge. The general work flow and system structure of privacy-aware participatory sensing systems is shown in Fig. 6. Application center (AC) receives data from participants and evaluates their quality. Trusted third party (TTP) sends encryption and decryption codes to participants and AC for privacy protection. Incentive scores are recorded either by AC or TTP, depending on different design goals. This TTP-based method is used in [69]–[71] and [73]. There are also some systems that do not contain TTP. For example in [73], the authors propose a TTP-free scheme, and the similar case is described in [74]. A detailed description is discussed as follows, and we summarize and compare them in Table V.

Zhang *et al.* proposed a pseudonym, encryption function to protect user privacy and incentive [69]. They used an one-way hash function and symmetric key algorithm to implement the system encryption. One-way hash function was an algorithm that took an arbitrary block of data and returned a fixed-size bit string. Symmetric key algorithm used the same cryptographic keys for both encryption of plaintext and decryption of ciphertext. The participant used his/her cloaked pseudonym $h(m_i)$ to send data, where m_i denoted pseudonym and $h(\cdot)$ denoted the one way hash function. AC received sensing data and resent the information with rewards and $h(m_i)$ to the participant. When he/she expected to gain rewards from the TTP, he/she must show the pseudonym m_i to TTP. As m_i was cloaked when being sent, malicious users could not obtain the participant's m_i, and thus the scheme protected participants' rewards from being stolen.

IncogniSense utilized periodic pseudonyms generated by using blind signature, and relied on reputation transfer between these pseudonyms [70]. In their proposal, there existed an application server (AS, acts as AC), and a reputation and pseudonym manager (RPM, acts as TTP) in the system. In the beginning, each participant picked a new pseudonym for each time period, which was used to report sensory readings to AC. It evaluated the sensing data and sent rewards of the participant to TTP. Before the next period started, the user transferred his/her current pseudonym to his/her next pseudonym, and transferred the incentive scores with next pseudonym and incentive tokens to prevent corruption. The TTP maintained a list of participants' presented pseudonyms along with their validity interval. It was protected against unauthorized access by using standard cryptographic primitives, and participants did not directly access their incentive accounts. Toward this end, a malicious user could not attempt to generate multiple pseudonyms to increase their incentive scores for a given interval, nor attempted to alter the incentive scores. Similar to [69], it deposited incentive scores in TTP, and generated pseudonym based on blind signature which was used in [73]. However, different from [73] that generated a mobile node's pseudonym just once, in [70] mobile nodes had to transfer their pseudonym after a period and their incentive scores needed to be added to their new accounts.

Similar to [69] and [70], Huang *et al.* also used pseudonyms to protect participants' privacy [71]. However different from the two, the TTP in [71] would anonymize a participant's time and location information before the participant was about to send the sensing data to AC, and resent it back with retrieved incentive scores that he/she earned before. This could protect a user's privacy from been stolen by malicious users.

The AC used a function to compute a participant's incentive scores as:

$$r = \exp^{b \exp^{c \times \left(\sum_{t'=1}^{t} \lambda^{t-t'} \times R_{t'}\right)}}, \tag{6}$$

where b and c control the growth rate of the r function with range between 0 and 1; t denotes the sensing time, t' denotes the anonymous time, and $R_{t'}$ denotes the rating to what degree a participant cooperates the AC. Designers cloaked users' temporal and spatial information for further preserving their privacy and protecting malicious users from identifying these pieces of information.

Sun *et al.* used TTP to select participants [72]. Platform employed the price-considered auction to deploy its incentive mechanism, where whether a participant would be selected or not highly depended on his/her bidding price and what subtask he/she took, that might leak his/her privacy information. In their proposal, bidding price and the type of sub-tasks was encrypted, and further signed by participants, before sending to the platform while being forwarded to the auction issuer (AI) to participate the incentive auction. If a participant was eventually chosen after the auction, he/she would send the information via the AI and then rewarded by the platform.

A system solution that when a requester sent a task to the AC, a participant would take the task if he/she wished to was proposed in [73]. The participant generated a random pseudonym to communicate with AC as a part of the privacy preservation process. The sensing data with a new, different pseudonym was then sent to the AC, which later paid a certain number of pseudo-credits to the reporting participant. The reason why AC used pseudo-credits was that it did not exactly know the real identity of the participant, and thus the AC updated the participant's credit accounts when he/she sent the pseudo-credits in a random time spot with his/her real identity. TTP in this system acted as a secret sending place, where it sent secret keys to AC for decryption, and sent secret request token, report token, and credit token together to the participant. The former two tokens were to make sure that each participant accepted and reported only one task at a certain time, the last token helped make sure that he/she could eventually receive the given credits. Compared with [69], the proposal in [73] deposited participants' credits in the AC but not TTP, where it used an one-way hash function for encryption similar as the one used in the TTP-based scheme like [69].

Li *et al.* also proposed a TTP-free scheme that distributed the TTP task to the AC and participants [73]. It used both a blind and a partially blind signature to generate tokens. The blind signature could aid a participant to obtain a signature from the AC on a message, and the AC did not know about the message being signed. A participant's credits were also deposited in the AC. The authors argued that in the TTP-based scheme, every phase could be finished within the scale of tens of milliseconds and consumed mobile phone about 0.05 joules to process each task. In the TTP-free scheme, the energy cost was slightly more than that of the TTP-based scheme which was 0.22 joules per task.

Similar to the TTP-free scheme in [73], Oscar *et al.* did not employ TTP in their participatory sensing system neither [74]. They focused on sensing data credibility and privacy preservation. A participant's reputation was not only used as his/her incentive reward, but considered as part of the evaluation process for sensing data quality. That was, when a new participant registered to the AC, it created a unique ID, and initialized an initial reputation for the new participant in the respective reputation database. The participant would cloak his/her ID when he/she sent the sensing data, which contained sensing environmental attributes such as sensing time, location, etc, and these pieces of information eventually influenced on how trustworthy the sensing data would be.

D. Summary of Theoretical Frameworks

Compared with the above mentioned theoretical frameworks, we conclude that:

- "Price-Decision-First" and "Data-Update-First" strategies benefit different shareholders in a participatory sensing system. The former benefits participants since they are aware of the amount of incentive they can earn before the data is uploaded, and then to decide whether to accept this task or not. Task publishers may prefer the latter strategy, because the amount of paid incentive can be decided upon the quality of collected sensing data.
- "User-centric" and "platform-centric" approaches aim at different design goals. The former focuses on ensuring the data quantity by recruiting its more participants and keeping them participating in future tasks. The latter pays more attention on the quality of collected sensing data, where information gain is expected to be maximized and overall sensing cost is expected to be reduced.
- Some of theoretical approaches are verified by field experiments, such as "Pick-A-Crowd" framework which was implemented with Facebook App OpenTurk to experiment [37]. Some of other theoretical approaches are not verified by experiments, such as Chou *et al.* verified their proposal by simulation [35].
- In these system models, the task publisher and platform are treated as one single entity, but in practice, they play different roles serving as content provider and network service provider, respectively. We shall discuss more on this aspect in Section VI.
- Most likely a TTP will be deployed in a privacy-aware participatory sensing system to protect participants' privacy. Some papers consider TTP just as an authority that deposit incentive scores. For example, in [69] and [73], participants exchanged their incentive scores from TTP. On the other hand, some authors treated TTP also as a pseudonym machine, e.g., in [70] and [71]. However the difference was that [71] anonymized the sensing data information but the proposal in [70] did not.

III. Applications and System Implementations

In this section, we review nine different applications for participatory sensing, and compare their features as shown in Table VI, from application schemes, incentive motivations and formats, and evaluation process. Finally, a summary is given to conclude this section.

TABLE VI
DIFFERENT APPLICATIONS FOR PARTICIPATORY SENSING

Application name	Application category	Incentive strategy	Sensing activity	Reference
MTurk	utility platform	monetary rewards	depended on tasks	[49]
TruCentive	parking information system	credit/monetary rewards	GPS	[50]
APISENSE	utility platform	credit	depended on tasks	[51]
Noisemap	noise pollution measured system	achievement and ranking	microphone and GPS	[52]
Ikarus	thermal hotspots detective system	competition	GPS	[53]
LiveCompare	price compared system	comparison	photos and GPS	[54]
Medusa	utility platform	monetary rewards	depended on tasks	[55]
TPS	Traffic prediction system	credit	GPS	[56]
w8L0ss	weight-loss intervention application	intrinsic incentive	N.A.	[57]

A. Applications for Participatory Sensing

Amazon Mechanical Turk (also called MTurk) was a famous platform served as a programmatic interface for tasks that were easier for humans than for machines, but most people considered it as a labor market [49]. It was a utility application for different tasks and requesters. A person or corporation acted as a task publisher who published tasks with a specified compensation (with limited budget). Participants could complete these tasks, and then he/she could earn some compensations as incentives paid by the corresponding publisher.

Hoh *et al.* presented TruCentive, which focused on encouraging participants to contribute parking availability (PA) information with high quality data, and preventing malicious participants from spamming the parking service with high volume of useless data [50]. TruCentive used system credits as incentives. A static reward was granted to a participant right after his/her information was accepted, and he/she would obtain another reward as a bonus, if the parking information was successfully confirmed by the consumer who bought it. A consumer might deny the fact although he/she had already parked successfully, and thus he/she could receive a refund. In this regard, a game-theoretic incentive mechanism was presented to address the malicious participants problem. The idea was that, if a consumer successfully parked at the traded spot, and he/she told the truth, he/she could re-sell this parking spot later through TruCentive, and earned more credits than if he/she lied. The MTurk platform in [49] was used in [50] in the evaluation phase, where they used a condition:

$$D + pX \geq R \geq D, \tag{7}$$

D is the constant reward, p is the probability of selling a PA and confirmed successfully, X is the bonus reward and R is consumer refund for unsuccessful parking. Considering service provider cost-benefit, the authors derived the constraints that:

$$D \leq R \leq \frac{1}{1+q}\left(L + (p+q)N\right), \tag{8}$$

where q is the probability that a PA is sold and confirmed unsuccessfully, and L is the platform pre-PA revenue, and N is consumer deposit for transaction. In the evaluation section, they set $N = \$2$, $R = \$1$, $D = \$0.20$, $X = \$2$, and found that when the resell probability p was as high as 90%, over 90% of the participants tended to resell their parking spots and be honest consumers. When p was as low as 10%, over 75% of participants tended to act dishonestly. By tuning the resell probability, together with other parameters, the participant's action was regularized in this framework.

APISENSE was a participatory sensing platform that helped scientists to collect realistic data sets from a population of voluntary participants [51]. Scientists could allocate amount of credits to indicate what type of data they wanted participants to sense. In turn, participants would receive reward, like monetary incentives and virtual credit. The authors argued that receiving sufficient large amount of sensing data in this platform was the best incentive to attract scientists. For participants who contributed sensing data, the more sensing data they contributed, the more incentive rewards they would receive. The authors also considered how to preserve participants' privacy, to prevent attacks on geo-spatial data, by blurring the reported data collection time and location using techniques like k-Anonymity [78].

In Noisemap, a smartphone was used as a noise meter to send noise information of the surroundings to an urban management platform [52]. The authors pointed out that two main challenges were how to successfully ensure data quality and quantity. To drive user engagement and improve data quality, four different incentive schemes were implemented in their proposal, categorized into internal or external incentives. Both of them used gamification theories [79] without any monetary incentives. *Internal incentives* meant that the application must reflect the participant's experience and set new goals to achieve. Two kinds of internal incentive method were designed. One was called *Statistics*, i.e., the complete feedback on users' measurement history; the other one was called *Achievements*, where the system could set new goals for users. *External Incentive* was also implemented in two ways: *Ranking* and *Rank*. That was, participants were rewarded by points, and points were used for a global ranking. In their proposal, a point P for one contributor was given by:

$$P = \sum_{m \in \{G\}} a \times e\left(H_{\text{area}}(m)\right) \times H_{\text{ay}}(m) \times H_{\text{bs}}(m), \tag{9}$$

where G denotes measurements, a is a constant, $e(H_{\text{area}}(m))$ is the exploration factor over the last 7 days in the area where participant m is located, accuracy H_{ay} is the location accuracy of m and bonus H_{bs} is given in certain bonus areas. Besides, *Ranks* were achievements that could be uniquely entitled to one participant.

Ikarus was a participatory sensing application that exploited sensory data collected during cross-country flights by paraglider pilots to study thermal effects in the atmosphere [53]. Data was stored in a flight log generated by a flight navigation device, and paragliders carried the flight navigation device during flights. To collect more data, the authors used a competition incentive mechanism to collect more flight logs that stored sensory data. One purpose of using flight navigation device was to collect GPS information in a flight log, including position, longitude and altitude, to prove that certain way-points had been passed. Paragliders preferred to use this record to compete with each others for fun. Then, the authors built a web community to rank (such as the numbers of way-points or one way-point nobody has ever passed) each paraglider's record, when they uploaded their flight log.

LiveCompare was a system based on participatory sensing with mobile devices to improve inter-store grocery price comparisons [54]. When participants aimed to compare the price of their product of interest in nearby stores, they used their phone camera to snap a photograph of its price tag and uploaded it with their GPS information to the system database. The photograph must have the bar code of this product to uniquely identify a product. The correlated GPS information helped LiveCompare send the price information of other stores which were near a participant's current location. To make sure the quantity of the system's data, the authors designed a "upload-first" comparison incentive mechanism. In this scheme, participants acted not only as requesters but also contributors. To evaluate this application, the authors conducted field work in seven different brick and mortar stores to show that price dispersion could be observed across a variety of grocery items, typical store price tags contain sufficient information to enable LiveCompare's infrastructure, and data transfer performance was reasonable over a typically used network.

Medusa was a platform that provided abstractions for specifying the steps required to complete a crowdsensing task [55]. It employed a distributed runtime system that coordinated the execution of these tasks between smartphones and a cluster on the cloud. When a requester wanted to publish a task, he/she submitted this task by using a programming language called MedScript which was specifically designed for Medusa. A worker manager, as one of Medusa recruitment component who used MTurk API, would recruit participants and manage monetary incentives after the task completion. The authors argued that, compared with some other participatory sensing systems, their proposal used less lines of code and shorter delay, to achieve more scalability, less overhead, and better robustness.

Traffic prediction system (TPS) was to provide accurate prediction of road traffic by using a credit based incentive mechanism [56]. Participants must buy the service of this system by using credits which they earned from uploading sensory data. The authors used a "dynamically credit-giving" mechanism, i.e., if a road was lacking in data, then credits of this road would be more than others. The better quality of sensory data participants uploaded, the more credits they earned. The authors used speed measurements to evaluate the data quality. That was, if a participant contributed his/her speed which was almost equal to the historical average data, then his/her data was of high quality.

w8L0ss was a weight-loss intervention application, that integrated self-determination theory (SDT) of health behavior change as intrinsic incentives [57]. SDT was a theory focusing on physically and psychologically adopted healthy behaviors and maintaining them over time. In SDT, intrinsic goals such as health, affiliation, and self-recognition tended to be directly connected to the satisfaction of basic psychological needs, and were typically regulated by more autonomous forms of motivation. w8L0ss allowed participants to record their activities, including self-weight, dietary, physical and coaching activities, that eventually contributed to the weight-loss. Clearly, participants who used w8L0ss aimed to lose weight and they most likely had good self-motivation. Therefore, this application did not need explicit (or extrinsic) incentives like real monetary incentive. Instead, it needed *intrinsic* incentives to keep them losing weight, and informed them of the gap between their achievement and goal. To this end, the authors proposed an intrinsic incentive method called "Achievement Level," that was, the participants set their goals which indicated how long they would spend in losing weight. When they finished their exercise in a phase, the incentive mechanism would compare their achievements with the initial goals. Then, it showed how much time the participants had spent in losing weight, and when they could achieve their goals. Mitchell *et al.* defined motivation or incentive as "a psychological process that caused arousal direction and persistence of voluntary actions that were goal directed" [80]. The exercise time information that the incentive mechanism showed to the participants could cause the participants voluntary actions, which meant losing weight in this platform.

B. Comparisons

1) Different Application Schemes: From the above proposal analysis, we observe that different types of participatory sensing applications are proposed and used in our daily life, and many of them eventually use MTurk to implement their monetary incentives. TruCentive, LiveCompare and TPS focus on serving people's daily life, while APISENSE and Medusa are based on cloud technologies to enhance data utilization. APISENSE focuses on scientific research, and Medusa features a formal programming framework for participatory sensing. Ikarus is a sport application for paraglider to find thermal hot spots. Noisemap is a noise pollution detection and presentation application, to help a city's environmental division find noise pollution districts. Finally, w8L0ss aims at reducing participants' weight.

2) Different Incentive Motivations and Formats: Incentive schemes used in these applications are different. Some are designed to directly pay participants as a reward, while the others aim to make them psychologically satisfactory. However, none of these incentive schemes can achieve some effect if what participants receive is not similar as what they expect and able to cover their sensing costs.

As shown in Fig. 7, there are monetary and non-monetary incentive mechanisms existed in participatory sensing applications. MTruk and Medusa using monetary reward to implement its incentive schemes, where some fees as a reward are always

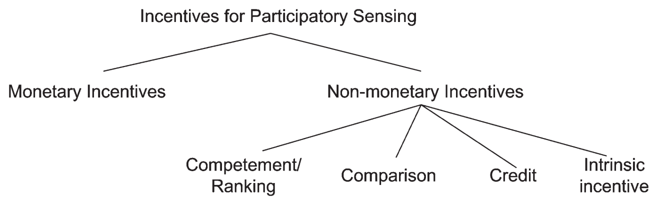

Fig. 7. Different kinds of incentives implemented in the existing applications.

paid from each task in order to compensate contributors who complete the task. TruCentive, APISENSE, Ikarus, Noisemap, LiveCompare, TPS and w8L0ss are non-monetary incentive applications, where some kinds of rewards but not real money are used. Specifically, credits are used in TruCentive, APISENSE and TPS. However, Ikarus, Noisemap and LiveCompare propose competition or comparison based schemes in their incentive mechanisms. On the other hand, w8L0ss application uses intrinsic incentive reward; TruCentive proposes a static reward plus bonus method to motivate data contributors, where the reward can be paid by either real money or virtual credit; TPS does not have a bonus reward mechanism compared with the employed incentives of TruCentive. Finally, incentive models are different among these proposals. Ikarus and Noisemap have ranking mechanisms, which LiveCompare does not have. Noisemap also has an "Achievements" scheme as the internal incentive mechanism, which Ikarus does not have.

3) Different Evaluation Process: The authors evaluate their applications in different aspects. Ikarus compares its performance with a raster model of thermal convection. Noisemap sets three different groups, as no incentives, internal incentives and all incentives groups, to evaluate its collected data quality and quantity. LiveCompare first demonstrates price dispersion existence, then evaluates data transfer delay, and finally location accuracy is tested. It does not compare with others, but evaluates itself in aspects of data utilization, accuracy and delay. Different with LiveCompare, Medusa evaluates its performance in aspects of language expressiveness, scalability, overhead and robustness to highlight its performance. **TruCentive focuses on information quantity and accuracy**, where the authors aim to find a balance point to make a satisfactory performance. Finally, TPS puts more attention on speed accuracy, considered as data quality, and the effect of encouraging participants to choose roads that is lack of contributed data.

C. Summary

We summarize the differences of the above seven applications and platforms from application category, incentive strategy and sensing activity, as shown in Table VI. We conclude that:

- Although participatory sensing has a long way to be part of our real life, it has already shown huge potentials in some aspects of our daily life, e.g., parking spot finding, noise pollution monitoring, scientific research assistance, etc.
- Monetary incentives are only one of many incentive mechanisms, to be simple and practical. If system designers use this mechanism in a proper way, a small amount of money can motivate participants to collect satisfactory amount of useful data as we mentioned in Section IV-C. Therefore, how to design a proper monetary incentive mechanism is a challenge for practical participatory sensing research.
- There are many other types of incentives besides real money, such as competition mentioned in Ikarus, comparison proposed in LiveCompare, achievement and ranking in Noisemap, and credit payment in APISENSE.
- The reason why the authors design incentive mechanism is that they aim to keep participatory sensing systems running, and a good incentive mechanism is one of reasons to make sure of satisfactory level of data quality and quantity.
- Among these applications and platforms, only APISENSE considers participant privacy, as an important issue in real life that has been discussed in Section II-C.

IV. Experimental Studies

Research efforts have been paid to explore the impact of different incentive strategies from empirical studies [42]–[48], [52], as summarized in Table VII. Specifically, since none of the above mentioned theoretical approaches have conducted field experiments to evaluate their efficacy, we next show how they are supported by the existing experimental studies.

A. Parameters

An experiment about finding out how to motivate participants to work harder in an enterprise was made in [42]. The authors created a crowdsourcing community inside IBM company with about 400 000 employees who spread over 160 countries within one year. The task for participants was translating sentences from English to other languages. Different from others, this experiment focused on finding out extrinsic and intrinsic motivations in a company.

To find out whether reciprocity could be used to effectively motivate user contributions in a participatory sensing system, Tomasic *et al.* made an investigation in [43]. This study recruited 8447 participants and took 10 months to make a real-time arrival information system. The authors selected the Tiramisu system [81] that allowed transit riders to crowdsource arrival information by sharing location traces on a cell phone. They used virtual credits as a way of incentives, where if a participant accessed the arrival information for the whole day, he/she would be awarded one virtual credit called "usage-point" (presented as a). If a participant contributed a location trace, he/she would be awarded one credit named "contribution-point" (presented as b). The authors used the ratio b/a to infer free-riding behavior. That was, when a participant's ratio exceeded a threshold, he/she was considered as a free-riding.

Micro-payment was one of the first to explore the performance of an incentive strategy on a real-world testbed [44]. It recruited 55 young individuals from a campus in the U.S. for five weeks. Participants were asked to take photos of garbage bins all over the campus to learn the status of recycling practices at this university. Through the platform of MTurk [49], monetary micro-payment was distributed to participants as an incentive tool for task fulfillment. The contributions of users were measured in terms of the amount of uploaded *photos*.

An experiment which compared the relative effects of micro-payments and weighted lottery incentive mechanisms was done by [45]. In this experiment, the authors took two days and recruited 96 participants in a conference using a collection of 50 Windows Mobile devices loaded with a virtual scavenger hunt game and distributing them among participants. Each participant must finish 10 tasks per participant in two days. The task contained a clue corresponding to one of the demo booths at the conference. When a participant felt that he/she had correctly decoded the clue, he/she proceeded to the associated demo booth and scanned the 2-D bar code through the application. A reward would be paid if he/she is successful.

Mao *et al.* made a comparison between volunteer and payment incentives, to indicate how financial incentives influenced the quality and efficiency of the output [46]. The experiment was an annotation task originally performed by volunteers in the Planet Hunters [82] citizen science project for an experiment with paid participants on MTurk [49]. Planet Hunter was a project whose goal was to find planets orbiting around extra solar planets or exoplanets. Participants examined stars produced graphs called “light curves” and “mark planets.” The authors recruited 200 participants who annotated about 14 000 light curves, and 356 participants who annotated over 17 000 light curves, respectively.

Noisemap involved 49 people for 7 weeks. Sound pressure levels by sampling the microphone were uploaded to the platform, together with the participants’ trajectories [52]. Unlike the monetary incentives in [44], virtual credits were given to participants as a return. The contributions of users were measured by the duration of *audio clips*.

Chon *et al.* recruited 85 people for an average of 79 days (i.e., 11 weeks) to do their experiment [47]. It was worth noting that its volunteers were from various social/cultural backgrounds with wide age range, compared with [44] and [52]. Participants’ phones sample the full range of built-in sensors automatically and photos were taken initiatively. Similar to [44], monetary rewards were given. The contributions of users were in the format of both *photos* and the duration of the *audio clips*.

36 participants were organized into 3 groups, named as “uniform group,” “hidden group” and “variable group” to do a three-day experiment [48]. The authors wanted to find out the relationship between micro-payment and incentive. Participants in this experimentation were asked to wear a wearable sensor and finish 20 questionnaires per day. Different payment schemes were deployed in different groups. Similar to [44] and [47], it allocated participants into one of three different groups. However it did not have a data competition group as the one in [47], neither did not have that many groups as in [44].

B. *Employed Incentive Strategies*

There was no monetary reward used in [42]. What the authors aimed to find out was whether the incentive mechanism was needed in a participatory sensing system, and if needed, what was the difference between psychological and physical incentive mechanisms. Therefore, they divided the experiment into 3 hypotheses. Hypothesis 1 was to create a portal and enlisted people. That was, the authors built the tool and just called participants to do the task. Hypothesis 2 was to talk about the crowdsourcing project that would eventually affect the company’s bottom line. In other words, the authors built the tool, called participants to do the task and told them the importance and the new feature of this task. What incentive the Hypothesis 3 proposed was to present the participants very clear extrinsic incentives like IPOD kits. That was, the authors built the tool, called participants to do the task and told them that they might earn some gifts as rewards.

Tomasic *et al.* first defined a rule where if a participant earned less than three usage-points without contribution-points, and more than six usage-points without contribution-points, this participant was considered to be free-riding [43]. Then, they divided these participants into three groups: The first group was called quid-pro-quo group (QPQ), which was defined in a way that if a participant was considered as a free-riding, he/she had to contribute his/her location traces before using this application again; the second group was called request group (Req), which was defined that if a participant was considered as a free-riding, he/she was required to share his/her location traces but could *still* use this application; and the last group was called control group, which was defined that it had no limit to use this application. The authors’ work similar as [42] that divided participants into three groups and did not use real money as incentives. But compared [42] which discussed the efficiency between intrinsic and extrinsic incentives, they focused on investigating whether reciprocity could be useful in participatory sensing.

In Micro-payment, all participants were divided randomly into five groups [44]. Group A offered each of its members a fixed amount of money as a return, but lay no requirements on how much/what they should contribute. Groups B, C, and D paid their members according to their actual contributions, but the unit payment for each photo was different. Specifically, Group B gave a low unit payment, group C gave medium-level payment and group D gave high payment. Group E paid its members in a competitive way, that was the unit payment for each member was decided by their “rankings.” As group B, C, D were paid according to their contribution, they somehow represented the efficacy of the IDF [20] mechanism. Meanwhile, group E could be seen as the experiment for the IFT [20] method.

In the comparison study [45], micro-payment group was defined as a group of participants who were compensated for each set of 5 tasks the completed. For each set of tasks completed by a participant, a \$5.00 gift card of a national coffee chain was given. In addition, participants were given a \$5.00 gift card for checking out a device for more than an hour, with a maximum compensation of \$15.00. In weighted lottery group, participants received a raffle ticket for every 5 tasks they complete, as well as a ticket for checking out a device for more than an hour. At the end of the day, tickets were drawn with winners receiving a \$50.00 gift card of the same national coffee chain.

There were volunteers who did not earn any payment at all and participants who would earn payment in [46]. Payment

TABLE VII
DIFFERENT INCENTIVE EXPERIMENTS FOR PARTICIPATORY SENSING

Participants	Last time	Sensing activity	Incentive Strategy	Outcome	Reference
400,000	1 year	none	spiritual and material rewards	0.015-6.194 words/day and participant	[42]
8447	10 months	GPS	virtual credit	19.1%-15.5% contribution rate and 41.4-50.3 days	[43]
55	5 weeks	photo and GPS	micro payments	3 - 13.5 picture/day	[44]
96	2 days	wifi	micro payments and weighted lottery	39-57 participants and 0.43-0.32 compliance rate	[45]
200	N.A	none	volunteer and payments	24.89 - 50 Secs/Task, and 1.250 - 1.964 Anno/Task	[46]
49	7 weeks	microphone and GPS	virtual credit	0.13 - 0.24 hours of audio clips/day	[52]
85	11 weeks	photo, microphone and GPS	overall payments	0.83 - 1.16 picture/day, 0.25 - 0.32 hours of audio clips/day	[47]
36	3 days	microphone and wearable sensor	micro payments	16 - 17 questionnaires/day	[48]

incentives were divided as "pay per task" where participants were paid for each task they complete, "pay per time" where participants were paid for each unit time that they spent, and "pay per annotation" where participants were paid for each object that they annotated on the smartphone.

All participants were divided into two groups in [47], the bonus payment group (BPG) and the data competition group (DCG). Members of both groups received the same amount of baseline payment, but BPG's high-ranking members received extra payments. The employed competitive payment strategy of the BPG group was very similar to Group E as in [44], while the non-competitive group was similar to Group A in [44]. However, unlike group E where competition losers would receive no payment, those of BPG still could have the baseline payment, which was consistent with the RADP [12] method.

In Noisemap, two different incentive schemes called "Internal Incentives" and "External Incentives" were implemented to attract user engagement [52]. The internal incentive scheme provided its members achievement titles as virtual credits, while the external incentive scheme provided its members the access to compare their virtual credits with others. In [52], we renamed the "external incentive group" as the "competitive group," and the "internal incentive group" as the "non-competitive group," to be consistent with the two former studies.

Musthag *et al.* deployed three different reward payment groups [48]. They were "Uniform" in which participants were rewarded a fixed amount for completing a micro task, "Variable" in which awarded vary randomly based on *a prior* distribution, "Hidden" in which awarded vary randomly, but the amount was not revealed until the micro task was completed. Compared with [44], Musthag had two groups less than that of [44].

In conclusion, the main differences among these experiments are:

- In [42], the authors provided spiritual and material incentives.
- In [45] and [46], the authors both aimed to find out how monetary incentive schemes perform compared with other schemes.
- In [44] and [48], the authors provided count-by-pieces monetary incentives. In [43], [48] and [52], the authors provided count-by-pieces virtual credits, and in [47], the authors provided the overall monetary incentives with baseline payment.
- Their common features were that they all compare the used competitive strategy with non-competitive strategy for performance studies.

C. Results Evaluation

As shown in Table VII, Stewart *et al.* divided the experiment into 3 hypotheses to translate [42]. In Hypothesis 1, designers just created a portal; in Hypothesis 2, they talked to participants to make them interested in this project; and in Hypothesis 3 they set extrinsic incentives. The translating results were, the average words per day per participant for Hypothesis 1–3 were 0.015, 3.797 (first week) and 6.194, respectively. The reason why we specifically marked the result of Hypothesis 2 as the result of first week, was that after the first week this number declined rapidly to 1.018 per day per participant. They concluded that right extrinsic incentive could be effective in participatory sensing but not necessarily be to cash.

Tomasic *et al.* divided participants into three groups focusing on investigating whether reciprocity could be useful in participatory sensing [43]. Quid pro quo (QPQ) forbade a free-riding, request group (Req) warned a free-riding, and control group had no limit to use this application. The average percentage of data contribution for QPQ, Req and control groups were 19.1%, 17.1% and 15.5%, respectively, and the average **lasting time** of these three groups were 41.4 days, 46.9 days and 50.3 days, respectively. From these results, the authors concluded that QPQ abandoned their use of the application for a higher rate than others. Although reciprocity could help increase data contributions, how to design it was still an open question.

Reddy *et al.* divided all participants randomly into five groups [44]. Group A offered a fixed amount of rewards. Groups B, C, and D paid their members according to their actual contributions, but the unit payment for each photo was different. Group E paid its members in "rankings." The results were, the average data contribution per user-day for Groups A–E were 3, 5.57, 6.7, 4, and 13.5 photos, respectively. The average contribution of Groups A–D did not change much between different days. However, it was worth noting that, the average contribution of Group E (the competition group) changed a lot, as it rose quickly in the first few weeks, and dropped quickly to nearly zero in the last few weeks. They concluded that monetary incentive was a more beneficial way than other motivating factors such as altruism or competitiveness.

Rula *et al.* aimed to compare the relative effects of micro-payments and weighted lottery incentive mechanisms [45]. Micro-payment group recruited 39 people and weighted lottery had 57 people; the number of participants who completed at least one single task were 23 and 39, respectively. Compliance rate were 0.43 and 0.32, respectively. They observed that participants in the micro-payment group spent more time traversing the conference area to find answers than those of the lottery group. Although weighted lottery group recruited more participants than the micro-payment group, it showed less compliance rate. The authors concluded that building on a participatory sensing incentive system needs to consider the application requirements, such as data quality, and the constraints of the task publishers like budget.

Mao *et al.* recruited 200 participants who annotated about 14 000 light curves and 356 participants who annotated over 17 000 light curves, respectively [46]. In the first experiment, the authors paid \$0.0453/annotation, \$0.0557/task, and \$0.08/minute, and the results are: for volunteers 50 seconds/task and 1.250 annotation/task, for "pay per annotation" scheme 29.13 seconds/task and 1.964 annotation/task, for "pay per task" scheme 24.89 seconds/task and 1.435 annotation/task, and finally for "pay per time" scheme 27.45 seconds/task and 1.454 annotation/task. Noted that paid participants completed tasks significantly more quickly than the volunteers, resulting in a much higher wage for both the task and annotation treatments. Moreover, participants in the annotation treatment were much more eager about marking transits than other participants. They concluded that paying participants can trade off precision, recall, speed and total attention of tasks. Therefore, it was important to design financial incentives to achieve desired participatory sensing results.

Chon *et al.* divided all participants into two groups, the bonus payment group (BPG) and the data competition group (DCG) [47]. Results showed that the average contribution of BPG was 1.16 photos and 0.32 hours of audio clips per user-day, as against 0.83 photos and 0.25 hours of audio clips per user-day for non-competitive groups. These results indicated positive effect of BPG was in effect with BPG outperforming DCG.

Schweizer *et al.* proposed two different incentive schemes called "Internal Incentives" and "External Incentives" [52]. The internal incentive scheme was the non-competitive group, while the external incentive scheme was the competitive group. The result from competitive and the non-competitive groups was clear, as an average of 0.13 and 0.24 hours of audio clips per user-day, respectively. The authors concluded increasing the amount of incentive schemes will keep more users motivated to participate and measure data.

Musthag *et al.* deployed three different reward payment groups: "Uniform" to award a fixed amount for completing a micro task, "Variable" to award vary randomly based on a prior distribution, and "Hidden" to award randomly while keeping the amount as not revealed until the micro task was completed [48]. The average completion rate were 86.28%, 86.92% and 81.68% for three groups, respectively. They argued that "Variable" can be a more powerful incentive strategy than "Uniform," while "Hidden" group did not perform well. The authors concluded that variable micro-payment incentive schemes provided powerful knobs where designers could tune in order to reflect different system performance metrics.

We next vertically compare these results and draw the following conclusions:

- From the result of [46], we observe that incentive mechanism is indeed needed, however the format and effect can be different. For example, [42] provided spiritual and material incentives, [44] and [48] provided monetary incentives, [43], [48] and [52] provided virtual credits.
- For participants' contributions, the proposals of [44], [47] and [48] received much more amount than that of [52], and the rewards in terms of virtual credit could be less efficient to motivate users than real money.
- Paying participants according to their actual contributions can lead to more sufficient data submissions than paying all of them with fixed amount, i.e., count-by-piece incentive strategy is better. This observation is also supported by comparing [44], [47] and [48], and [47] offered more rewards but received less data, since it paid the same amount of rewards to all participants.
- Competitive incentive strategies are more efficient than non-competitive ones, e.g., IFT [20] could be more efficient than the IDF [20] method since it distributed incentives in a more competitive way. However, the result of Group E in [44] and that of BPG in [47] were different: Group E's members gradually dropped out, but BPG's members were making lower but still some contributions. This was due to the mechanism used where competition losers received baseline payments in BPG, while there were no payments for Group E members if no contribution. Therefore, the proper amount of rewards to competition losers, even if they made no contribution, might keep them participating for future tasks, as confirmed by RADP [12].
- An interesting fact revealed by Group B, C, D in [44] was that, the amount of submissions did not increase with the increase of unit payment. Members in Group D received highest unit payment, but contributed smallest photo amount. We believe this is caused by the experimental setting, where participants cannot transfer from one group to another, and no more new participants are recruited so that it lacks a certain degree of competition inside a group.
- None of these incentive strategies is computationally complex, nor they need a lengthy user negotiation phase. It is interesting to observe that most incentive strategies adopted by experiments are fixed price methods, since such a method is light-weight and can be easily implemented on participants' energy-constrained smart devices. On the other hand, as vast theoretical incentive mechanisms are built based on the reversed auction based method [12], [14], [16], [28], [29], the verification of such methods through field experiments should also be investigated.

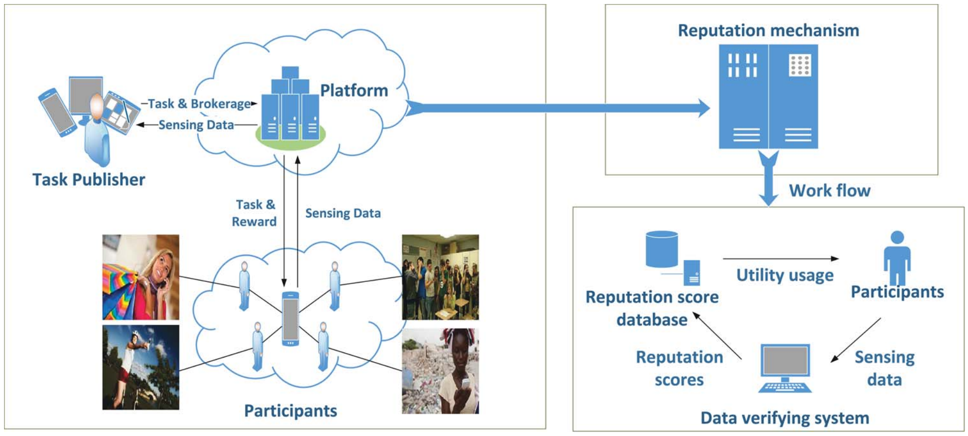

Fig. 8. The work flow of reputation systems.

V. Using Reputation Schemes in Participatory Sensing

There are some usages of reputation in state-of-art research activities, e.g., the incentive strategy in [70], [71], [73], [74], "reputation to data quality" in [83]–[85] (where reputation scores are mainly used to choose trustworthy sensing data), and "reputation to select participants" in [86]–[88] (where reputation scores are mainly used to select trustworthy participants). The main functionality of using reputation is to find out the accurate and true sensory data and avoid malicious participants as much as possible. Comparing with rewards that represent and characterize the transient, one-time quality of the collected sensing data, a participant's reputation is rather a long-term, accumulated metric to identify the quality and trustworthiness of a participant's sensory data. That is, the better quality the sensory data is from a particular participant, the more reward he/she can earn, and in turn more reputation scores he/she is evaluated.

Toward this end, reputation system is also a key part of the participatory sensing platform. As shown in Fig. 8, its work flow is as follows. First, a task is published. Second, the platform needs to choose who are going to help this task from a pool of participants. When their reputation is explicitly considered, the system will access their reputation score database and use them as the input to the compute a predefined utility function, e.g., to choose those participants who have high scores, to use reputation scores to weight sensory data, etc. After the data are collected, data verification system will verify the correctness and trustworthiness of these sensing data, and calculate a new reputation score. Finally, the former accumulated reputation scores are updated by considering the new score and uploaded to the database. The updating method may vary from system to system.

A. Using Reputation Scores to Evaluate Data Quality

Amintoosi *et al.* used the concept of "quality of contribution" (QoC) and "trust of participant" (ToP) to evaluate a participant's sensing data, and this evaluated data was called trust of contribution (ToC) [83]. If a participant's ToC values were higher than a predefined threshold, then he/she would be rewarded and the reputation scores, denoted as $trust_{RP}$, would be added. Alternatively, $trust_{RP}$ would be reduced when ToC values were less then this threshold, and in turn he/she would be penalized. The authors also used state-of-the-art methods to evaluate the QoC, including image processing algorithms proposed in [89] and outlier detection algorithm [90] for sound-based sensing tasks. The authors considered many detailed attributes to calculate ToP, including a participant's expertise, response time, locality, friendship duration, and interaction time gap between participant and requester. QoC and ToP were computed together by using fuzzy logic and the output score was the ToC. Furthermore the requester could also express his/her evaluated trust of the participant's contribution using the Requester Evaluation (RE). The platform combined the requester's RE with the participant's ToC and his/her former reputation scores together to evaluate the new reputation scores and then stores this new scores in the database.

Amintoosi *et al.* proposed a recruitment framework for social participatory sensing [84]. Although it employed social networks to recruit a participant's friends and friends of friends (FoFs) to participate, it mainly used ToC to evaluate their sensing data. That was, if a participant's ToC value was higher than a predefined threshold, then he/she and correlative FoFs would be rewarded and their $trust_{RP}$ would be increased, or their $trust_{RP}$ would be reduced when ToC values were less then this threshold and they would be penalized. Besides the attributes mentioned in [83] which were considered to calculate ToP, the authors in [84] also considered the relationship of friends and RE (as mentioned in [83]), which were two new attributes to calculate it.

Albers *et al.* used a utility function $S(x)$ in their MAA system (as mentioned in Section II-A1), as the sensing data quality index to aid the platform to select the most appropriate sensing data [85]. Many attributes of the sensing data were considered in $S(x)$, including the distance, sensing time, sampling frequency, positioning accuracy and user credibility, etc. Besides, the participant's reputation was only one of many attributes. The utility $S(x)$ is computed as:

$$S(x) = \sum_{i=1}^{n} w_i S(x_i), \tag{10}$$

where $\sum_{i=1}^{n} w_i = 1$, w_i is the weight factor, n is the number of relevant attributes decided by the system operator, and $S(x_i)$ denotes each valued attribute. The larger $S(x)$ is, the more chance the participant will be selected.

B. Using Reputation Scores to Select Appropriate Participants

Huang *et al.* proposed a participant selection strategy when considering their reputation scores [86]. They designed a "watchdog module" and a "reputation module." The watchdog module was used to choose participants, verify data correctness and send cooperative rating to reputation module as an input to calculate new reputation scores. The reputation module stored participants' reputation scores, sent these scores to the watchdog module to calculate correct data, and helped watchdog module filter out those participants whose reputation scores were below a threshold. The authors used majority voting numbers and reputation scores to decide which sensing data should be accepted. When the correct data were generated from the watchdog module, the corresponding cooperative rating $p_{i,k}$ of every participant, where i denoted the participant and k denoted the time epoch, was sent to reputation module to calculate reputation scores, by using Gompertz function [91] as:

$$R_{i,k}(p'_{i,k}) = \alpha e^{\beta e^{\gamma p'_{i,k}}}, \tag{11}$$

where α, β, and γ are scaling factors, and defined by the platform. Parameter α specifies the upper asymptote, β controls the displacement along the x axis and γ adjusts the growth rate of the function. If a participant's reputation score fell below the threshold, the reputation module would feedback this information to the watchdog module, and then the platform would not accept his/her sensing data unless their sensor values were beyond the threshold.

Yang *et al.* proposed a framework to calculate the reputation information and used it to select participants [87]. They considered three aspects to rank participants, as "direct reputation (DR)" based on a participant's previous data quality records and performance, "personal information (PI)" written by the participant himself/herself, "indirect reputation (IR)" including subjective information such as community trust and requester's trust. When a requester defined explicit criteria (such as a participant' age or location demand), the system would use participant's DR, PI, and IR scores to calculate a value which was used to rank the participant into four levels (Very trustworthy, Trustworthy, Untrustworthy and Very untrustworthy). Finally, the requester could select participants from these levels.

Ganeriwal *et al.* designed a reputation-based framework called "RFSN," to ensure data quality [88]. The underlying model of RFSN was from the *Decision Theory* [92] in economics, where malicious or faulty participants acted in a completely arbitrary manner instead of acting rationally as incorrectly assumed in many other reputation systems. Similar to [86], RFSN also had two key building blocks: "Watchdog" and "Reputation." Watchdog was responsible for monitoring the actions of other participants and characterizing these actions as cooperative or non-cooperative in a data transaction, by associating a level of confidence that ranges within (0, 1). Different applications might have different criteria for defining a proper confidence level. Specifically, this paper implemented one possible method in detail. That is, distance-based outlier detection. Therefore, the input to this block was a set of data readings, and the output was a rating X for each data reading ($X \in \{0, 1\}$). However, different from [86], Watchdog did not reject participants, but rather left participants themselves to decide which neighbors were trustworthy. Using these ratings together with some other external evidences, RFSN evaluated the trustworthiness of other participants and their data. It continuously maintained the reputation of participants. The authors adopted a classical beta-binomial framework for estimating reputations [93], [94]. That is, suppose a transaction occurred between participants i and j, and θ denoted the reputation of j held by i. Instead of a solid number, θ was assigned a beta distribution:

$$p(\theta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \theta^{\alpha-1}(1-\theta)^{\beta-1} \tag{12}$$

where $0 \le \theta \le 1, \alpha \ge 0, \beta \ge 0$ and α, β are defined by designers. $\Gamma(\cdot)$ is a typical gamma function [93] in statistics. Thus, RFSN used the mean of θ as the reputation score. Given θ, the authors then modeled the binary ratings as Bernoulli observations with success probability θ. The authors then proved that posterior probability of θ after a transaction also had a beta distribution, with only slight changes of parameter α and β. Therefore, the proposed reputation system required i to maintain only these two parameters to describe the reputation of j with very simple update rules as each new transaction occurred.

C. Comparison and Discussions

As shown in Table VIII, the reputation plays an important role to help the platform select sensing data and/or participants. As discussed in Section V-A, the requester's trust is used as one attribute to evaluate participants' data quality in [83], [84]. Amintoosi *et al.* in [84] proposed a participant recruitment method that employed social networks to recruit a participant's friends and friends of friends (FoFs) to participate, while the authors in [83] did not mention it. The authors in [86], [88] both proposed a watchdog block to detect invalid data. However, the block in [86] rejected a participant's sensing data when his/her reputation scores fell below a threshold. Yang *et al.* ranked the participants by using their reputation scores into some levels to allow the requester to choose, instead of the system [87].

VI. Future Directions

In this section, we further identify 10 critical challenges and opportunities on incentive mechanisms for participatory sensing, with respect to the stochastic characteristics of participatory sensing systems, the information gain of task publishers, setting initial auction threshold, deploying cloud computing based platform and multiple incentive schemes, as well as participant's reputation, energy efficiency and convenience, etc.

TABLE VIII
DIFFERENT REPUTATION USAGE

Purpose	Features	Reference
data quality weighted index	publisher involved and more detailed attributes considered into ToP	[83]
	publisher involved and recruitment was mentioned	[84]
	took data price into consideration	[85]
participant chosen index	set a watchdog module and rejected low reputation participants	[86]
	made publisher choose participants	[87]
	set a watchdog block and reputation stored in neighbor's database	[88]

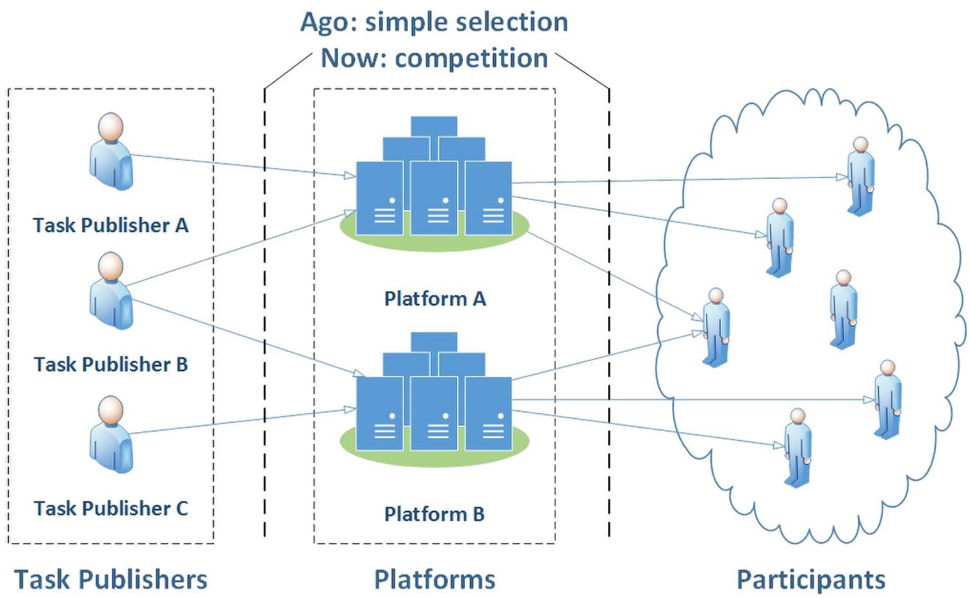

Fig. 9. The participatory sensing system with multiple platforms, where the task publishers can choose different platforms for their sensing tasks.

A. Separating Task Publishers and Platforms

As discussed above, task publishers and the platform should be treated separately, since in practice they are two different independent economical entities. The same task publisher may send tasks to different platforms in a nearby area, and these platforms can resort help from different groups of participants based on different collected sensory data levels (such as old and new, coarse- and fine-grained data, etc.; see Fig. 9). Then, users can be associated with different prices according to different sensory data levels, to optimize the overall revenue being aware of participants' heterogeneous sensing capabilities.

By introducing multiple platforms, competition among them will become another research issue. On one hand, different platforms are competing to accept sensing tasks from task publishers. An optimization problem can then be formulated to minimize the sensing costs under the constraint of data quality requirements for each platform. In addition, a new challenge arises for the platform as how to precisely predict the cost when providing sensing results of different quality. On the other hand, different platforms will be competing for recruiting and maintaining participants. Existing incentive strategies assume that the platform plays a dominant role and participants are disadvantaged and required to lower their bid prices to get involved. By introducing competition among platforms, each will be obliged to balance their price offers according to the tradeoff between higher price to recruit more participants and lower price to increase its profit. In this way, participants' benefits can be protected, and more users may be expected.

B. Leveraging Historical Sensory Data for New Tasks

It is possible to allow platforms to sell the collected historical data to other platforms/task publishers, since tasks may overlap in spatial and temporal dimensions, and the only difference can be the data quality such as accuracy. Along this direction, a new incentive scheme should be proposed since not only participants but also the platform will receive rewards. Therefore, the issue of how to collectively optimize both of their benefits should be investigated. Questions still remain though as to what extent platforms should purchase the historical data in order to secure a crowd of participants for future, new tasks (that cannot leverage existing data). A dynamic scheme that can achieve long-term equilibrium is needed from this angle.

C. Improving Data Quality by Proper Incentive Allocations

Environmental monitoring is one of the important applications of participatory sensing, which requires spatio-temporal samplings with coverage requirement. When the incentive budget is inadequate to obtain all data, the missing data will be reconstructed by interpolation methods [64]. Data reconstruction is performed considering the fact that the environmental data in nearby subregions are usually correlated. Existing incentive approaches ignore this spatio-temporal distribution of expected samples, and ultimately may cause missing data in certain regions and lead to inaccurate data reconstruction results from interpolation. A novel incentive mechanism is needed in this regard. On the other hand, incentive mechanism is needed in data quality aware systems to stimulate participants' involvement and enhance the system robustness [95]. Though Song *et al.* proposed a data quality aware strategy with participants' reward [96], they did not explicitly consider that participants incentive requirements could be dynamically decided according to the amount of data they provide.

Furthermore, unlike [29], a scheme should be proposed to avoid requesting full coverage data samples, since it might cause extra cost to the participant's sensing capability. A step forward is to explicitly take into account the multiple participants' mobility pattern (i.e., trajectories), their sensing coverage, acceptable price offer, and spatio-temporal task requirement, since this scheme can optimally distribute the entire incentive budgets among participants.

D. Energy-Aware Solutions

In existing incentive mechanisms [20], [30] and [73], the authors had no explicit investigation into the energy level of participants' smart devices, and they all modeled the cost of participation on the basis of the absolute power and bandwidth usage. Though Liu *et al.* had employed incentive to help balance data quality and energy efficiency [97], they did not consider phone usage and mobility patterns, etc. However, the inconvenience during the participation procedure can be the major concern that prevents user engagement. As revealed by an online questionnaire we conducted recently [98], participants' remaining energy level and when their device can be recharged are two essential impact factors on their willingness to participant in sensing tasks, and thus further impact their incentive expectations. A novel optimization goal that drives a new incentive mechanism should be designed to maximize the platform's revenue by allocating smallest, but satisfactory amount of rewards to participants, in aware of their remaining energy levels, phone usage and mobility patterns.

E. Calculating the Actual Reputation of a Participant

Since the system may not be able to identify the ground truth of a participant's reputation in participatory sensing systems, the system has to accept certain amount of sensing data to predict the correct data that may cause data redundancy issues. Redundant sensing data waste a large amount of manpower and may cause the platform cost higher. Toward this end, how to discover the actual reputation of a participant without knowing the ground truth as *a priori* but still in a low cost way is quite challenging. In this regard, designers can use correlative (spatially and/or temporally) sensing data to verify another sensing data's quality, and Kriging Theory [99] can be employed to reduce data redundancy.

F. Leveraging Reputation Scores to Design Incentive Schemes

As shown in Fig. 10, there is a clear relationship between the employed reputation and the incentive mechanisms. When a participant's sensing data is sent to the platform, its quality will be evaluated. This quality score can be considered as a basis to compute participant's reputation score, as well as to aid the incentive allocation decision made by the platform. Meanwhile, the participant's reputation score will further influence how much reward a participant can earn. For example, if the participant always contributes high quality sensing data, his/her reputation score will be higher than those whose contributed data quality is lower. Higher reputation score can also be exchanged as an "extra" incentive reward (or bonus) to motivate participants to contribute more high quality sensory data in future tasks.

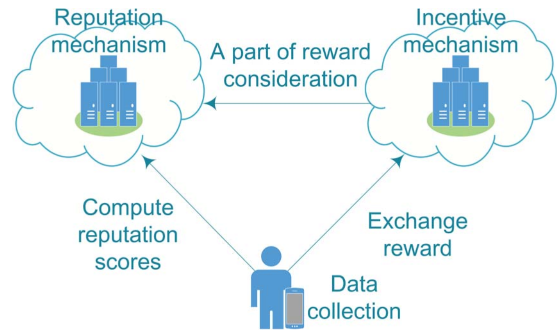

Fig. 10. Weighted sensing data will be sent to the reputation mechanism (left side) to be calculated reputation scores, in the meanwhile it will be sent to the incentive mechanism (right side) to be calculated incentive rewards. Reputation scores will influence incentive rewards as a part of consideration.

G. Middleware and Application for Automatic Bidding

Participatory sensing applications either require sufficient data automatically collected by sensors embedded on smart devices, or rely on users' intentional behaviors. However, current incentive strategies either decide the incentive payments without negotiating with participants, or require fussy negotiation procedures such as bid-price auction that requires participants' full engagement, thus causing disturbance to participants. Middleware and application level solutions on smart devices are therefore needed to learn a user's bidding history, and automatically decide bid prices which matches his/her expectations. In this way, auction is performed in the background and users are least disturbed.

H. Set Proper Bidding Price Threshold in Auction-Based Incentive Mechanisms

One drawback of auction based incentive mechanisms is that the platform has to collect all bidding prices or all the sensing data to compute the data quality threshold, and then decides which ones to accept. Participants have to wait for the platform's offer/decision for a long time. Although this method seems can gain high quality sensory data under limited budget, participants have to wait and they could be losers at the end, which is not ideal to keep them in the system. Zhang *et al.* in [21] and Zhao *et al.* in [22] named the above method as "offline bidding," and both of them proposed "online bidding" methods. However, there was still a drawback. That was, they either set a man made price threshold themselves at the beginning, or just based on first set of selected participants' bidding price or data quality to determine this threshold. That was, since the platform did not set exact bidding price or data quality threshold at the beginning, the first batch of participants either earned more/less than they deserved. This might waste platform's profit or lower down the trustworthiness of the sensory data. Therefore, how to decide the beginning bidding threshold in a more reasonable way needs further investigations.

I. Building Participatory Sensing Systems in a Cloud

When there are large numbers of participants in a participatory sensing system, they send their sensory data to the platform simultaneously that may cause sudden overload increase to the platform's storage and processing capabilities. In this regard, cloud computing related technologies can be leveraged to solve this Big Data problem. For example, Apache Kafca [100] can be deployed at the platform to provide realtime publish/subscribe based messaging services, and then Apache Storm [101] can be used as realtime data processing engine. After storing them in an HBase [102] column-based database for persistence, Apache Hadoop Map/Reduce technology can be used for processing/analysis distributedly across different virtual/physical machines.

J. Multiple Incentive Schemes Co-Existence

As mentioned in the survey [77], different participants might prefer different kinds of incentives, however current solutions only employ one single incentive mechanism. Although Scekic *et al.* proposed a modularization incentive mechanism where incentive schemes could be modeled depending on different participatory sensing environments in [11], it was still one single mechanism. Multiple incentive schemes allow different participants earn different types of rewards at the same time, however facing challenges on how to decide what type of incentive reward should be provided to which participant, and whether this decision is made decided by the platform or from the participants, in order to maximize their own benefits respectively. When a new participant arrives, the platform should be able to flexibly integrate existing schemes into a new scheme that is personalized to the new user according to his/her preferences.

VII. Conclusion

Incentive mechanism is a key design element of novel participatory sensing systems. In this paper, we extensively survey the state-of-the-art solutions and open up a few interesting future research directions. First, we classify existing theoretical solutions according to their design goals and also their incentive negotiation procedure, and review in detail the most recent representative research activities. Then, different kinds of participatory sensing applications and implementations are presented. Third, existing experiments are also compared in terms of their settings, employed strategies and results, and certain conclusions regarding how they support the existing theoretical frameworks are drawn. Last, we discuss trustworthiness of sensing data in participatory sensing and the relationship between reputation and incentives. Finally, we propose a few interesting future directions that include involving multiple platforms for participatory sensing, leveraging historical sensory data, improving data quality by proper incentive allocation, energy-aware, the relationship between reputation and incentive, middleware solutions for automatic bidding, flexibility to the participants selection, cloud computing for incentive mechanism and modularization incentive mechanisms.

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