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Intelligent Gaming for Mobile Crowd-Sensing Participants to Acquire Trustworthy Big Data in the Internet of Things

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***Abstract*—In mobile crowd-sensing systems, the value of crowd-sensed big data can be increased by incentivizing the users appropriately. Since data acquisition is participatory, crowd-sensing systems face the challenge of data trustworthiness and truthfulness assurance in the presence of adversaries whose motivation can be either manipulating sensed data or collaborating unfaithfully with the motivation of maximizing their income. This paper proposes a game theoretic methodology to ensure trustworthiness in user recruitment in mobile crowd-sensing systems. The proposed methodology is a platform-centric framework that consists of three phases: User recruitment, collaborative decision making on trust scores, and badge rewarding. In the proposed framework, users are incentivized by running sub-game perfect equilibrium (SPE) and gamification techniques. Through simulations, we show that approximately 50% and a minimum of 15% improvement can be achieved by the proposed methodology in terms of platform and user utility, respectively, when compared to fully-distributed and user-centric trustworthy crowd-sensing.**

***Index Terms*—Ambient intelligence, Data acquisition, Data analysis, Distributed computing, Intelligent sensors, Internet of Things, Mobile computing, Game Theory, Crowd-Sensing, Gamification.**

I. Introduction

IN the Internet of Things (IoT) Era, crowd-sensing (MCS) has emerged from large-scale participatory sensing which requires an implicit collaboration between crowd-sensing platforms and sensing data providers, i.e. the participants [1], [2]. Participants act as service providers in crowd-sensing campaigns by only using their smart mobile devices such as smartphones, tablets and wearables. These devices are equipped with various built-in sensors such as GPS, camera, accelerometer, gyroscope and microphone. Furthermore, the widespread use of these devices unveil the potential of them being an integral part of the IoT sensing. As stated in [3], because the IoT consists of massive amount of uniquely identifiable heterogeneous devices with communication, sensing and computing capabilities, the IoT architecture faces several challenges concerning the acquisition, processing and storage of big data streams.

In 2015, more than 1.4 B units of smartphones were reported to be sold worldwide [4], while 232 M units of wearables were sold in 2015 with a projection of 322 M unit sale in 2017 [5]. Various phenomena such as air pollution, water quality, road condition for smart transportation, public safety and emergency preparedness can be collaboratively sensed through these devices in a participatory, or opportunistic manner [6], [7]. Mobile crowd-sensing has been attracting the IT industry for various applications. A research consortium between IBM, University of Illinois and University of Minnesota has developed a middleware crowd-sensing platform which is called Citizen Sense [8]. Google has developed a crowd-sensing application called Science Journal, which is available via Play Store [9]. Science Journal exploits various built-in sensors in smartphones to acquire data regarding users' interests. The collected data undergoes real time analytics. Based on these phenomena, mobile crowd-sensing is listed as a critical component of the IoT [10].

Increasing popularity of the crowd-sensing applications introduced in mobile platforms implies that tremendous volumes of data need to be processed, analyzed and managed in order to extract context-aware information and facilitate decision making procedures [11]–[13]. According a report by Cisco [14], smart devices are predicted to generate 98% of the mobile data traffic and monthly mobile data traffic is forecast to reach 30.6 Exabytes by 2020. Recently, researchers have started tackling data quality assessment [15] especially in visual crowd-sensed data, and data quality-aware incentives in mobile crowd-sensing in order to avoid unnecessary rewards made to participants [16]–[18]. As the advent of Internet of Things (IoT) concept enables mobile crowd-sensing via built-in sensors of everyday mobile devices, uncertainty in the quality of crowd-sensed data is complicated since the recruited participants and their crowd-sensors are not professional/dedicated. While the quality of sensory data can be modeled as a function of the sampling rate, in these scenarios, it can be any random number. In order to deal with uncertainty in these scenarios, online learning approaches

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have been proposed to acquire the statistical information about the sensing values throughout the sensor recruitment process [19]. In [20], uncertainty propagation in distributed sensing has been modeled via Bootstrap-based methodology in order to improve system accuracy. Therefore, the integration of big data analytics into mobile crowd-sensing to improve the quality of the aggregated data – and consequently the quality of provided services – presents an important research area.

Effective user recruitment is a key function to achieve the desired performance of MCS platforms [21]. Therefore, it is imperative to incentivize users to promote participation [22], [23]. Proper recruitment policies allow selection of users that are able to fulfill sensing tasks with high accuracy while minimizing the system costs. On one hand, the central platform organizes and assigns tasks, thus sustaining a monetary cost to recruit and reward users for their contribution. On the other hand, users sustain costs for their contributions in terms of energy consumed for sensing and data subscription plan use for reporting [24]. Several incentive strategies have been proposed in the literature with the aim of addressing the trade-off between platform and user utility [25]. In [26], the requirements of an effective incentive design have been listed as compatibility, individual rationality, and efficiency.

When data analytics are applied to the aggregated data, the quality of information is closely related to the trustworthiness of the acquired data. In a typical mobile crowd-sensing scenario, the central platform matches sensing tasks with suitable participants through the *recruitment* process [27]. By applying proper recruitment policies, users that are able to fulfill sensing tasks with high accuracy can be selected, thereby minimizing platform operating costs. On the other hand, users incur costs for their contributions in terms of energy consumed for sensing and data subscription plan use for reporting.

Recruitement of reliable users requires realistic incentives to attract a sufficient number of users to the platform; several incentive strategies have been proposed to provide a mutually-beneficial platform for both the users and the platform [25]. Gamification is a widely adopted technique to increase user participation in user-centric systems [28], [29]. Nowadays, popular social platforms such as Foursquare, Twitter and Stack Overflow apply gamification in their application environment. Gamified incentives award *badges* to users. Badges stand for virtual rewards that are meant to provide a sense of accomplishment in the users and to motivate them to participate actively and continuously [28].

Analyzing user behavior is a crucial aspect of gamification-based user incentives [30]. Besides the utility of crowd-sensing platforms and participants, *trustworthiness* of the sensed big data is essential for critical applications such as public safety [1], crisis management, and disaster preparedness [31]–[33]. User reputations are key indicators of data trustworthiness in mission-critical crowd-sensing applications. The presence of malicious users introduces the risk of modified or altered data to deliberately spread disinformation. Through anomaly detection techniques, mis-behaving users can be detected, and their reputation is reduced [34]. Thus, a key objective of a crowd-sensing platform is to determine the level of reliability/trustworthiness for each user. To this end, user trustworthiness and reputation need to be stored and dynamically updated on the basis of the quality of contributed data.

An interesting challenge pertaining to the quality of data – and user reputation – is the possibility of inaccurate sensor readings (e.g., malfunctioning sensors in a user's smartphone) causing an incorrect classification of a user as *malicious*, rather than *inaccurate* or *invalid* [31], [35]. Furthermore, because of the limited communication capability of the acquisition network, intermediary cloudlet —or concentrator— devices exacerbate the security concerns that are associated with the acquisition network [36]–[38]. These concepts alone present different research areas; in this paper, we will make the simplifying assumption and will treat both cases as the same.

In this paper, we formulate a game theoretic approach to recruit smartphone users, in which participants with higher reputation are considered winners of the user recruitment phase. Although there is preliminary analysis in gamification-based crowd-sensing [39]–[41], this topic needs significant further exploration. We build on our recent study in [42], where users are incentivized via a repeated Subgame Perfect Equilibrium (SPE) in a three-step recruitment process. The first step is user-task matching via a reverse auction whereas the second and third steps are collaborative decision making (i.e., SPE), and badge rewarding for users with high reputation, respectively.

In this study, we propose a game theoretic vote-based user recruitment in detail and investigate the impact of environmental settings on platform and user utilities, as well as the trustworthiness of the acquired data via crowd-sensing. To this end, we study the impact of initial reputations of users on platform and user utility, as well as the awards made to malicious users. The motivation behind this study is that the user reputations evolve in time and estimating initial reputation of a participant becomes a challenging issue. Furthermore, we study the impact of similarity scores of the data reported by participants on user and platform utility under normal conditions, where users receive positive or negative votes from their neighbors that sense the same phenomena. We also investigate the platform and user utility effect of different badge rewarding mechanisms for highly reputed participants. We evaluate our proposed framework via extensive simulations and compare it to our previously proposed user recruitment scheme [43]. Our proposed framework improves platform utility by up to 50% and average user utility by 15% as compared to our previous work.

The rest of the paper is organized as follows. Section II presents background on big data and mobile crowd-sensing and motivates the need for trustworthiness in user recruitment and incentives. Section III presents the proposed trustworthiness-driven and gamification-based users recruitment model in detail. Section IV provides performance evaluation via extensive simulation results under various case studies. Section V concludes the work and outlines future research directions.

II. Background and Motivation

In [44], the authors present a comprehensive overview on urban sensing. Based on the role of users and how the user is involved in sensing tasks, two main approaches, namely participatory and opportunistic sensing are defined. Users are self-aware about sharing data with the others in participatory sensing but in opportunistic sensing, mobile devices are involved in the decision making process instead of the users. In [45], a framework has been proposed to combine the strengths of both paradigms.

Mobile crowd-sensing is a new sensing paradigm which incorporates built-in sensors of mobile devices and human intelligence to monitor, share, analyze big and heterogeneous data about diverse phenomena. Data provided by mobile crowd-sensing is used to design a variety of applications according to individual or group activities to model their behavior and predict possible solutions for different patterns. Personal and community sensing are the two primary categories under mobile crowd-sensing applications according to a categorization based on the type of monitored events [46].

The integration of big data analytics, mobile crowd-sensing, cloud computing, IoT, and wearable technologies promise to enable applications with broader impacts such as environmental monitoring [47]–[49], infrastructure management and social computing [50], road condition monitoring [51], sensor-annotated video surveillance [52], and remote health monitoring [53]–[55]. For example, the *Flysensing* application is a remarkable representative of social crowd-sensing, which runs on passengers' smartphones en-route to share data about safety, health monitoring, and surveillance of events in the air [56]. Social crowd-sensing concept has been introduced to partition huge sensing tasks to a network of participants [57].

In [58] the authors formulate a four-stage life cycle for mobile crowd-sensing applications with the following stages: Task creation, task assignment, individual task execution and crowd-data integration. In each stage, the following 4W1H framework is taken into account: What phenomena should be sensed, when and where the assigned task should be sensed, who is responsible for collecting data and how the sensing task is divided between users as well as how collected data is communicated to the recruiter.

A. Big Data and Mobile Crowd-Sensing

During the last decade, a tremendous volume of data has been generated by means of Information and Communication Technology (ICT). According to Zikopoulos et al., the global data volume is expected to reach 35 Zetabytes by the end of 2020 [59]. As reported in [60], mobile crowd-sensing generates a substantial volume of heterogeneous big data that makes it insurmountable for relational databases to handle. Combination of big data analytics and mobile crowd-sensing introduces new challenges to assure the veracity of the acquired data. This motivates the development of novel methods for the storage, management, and processing of crowdsensed data by using predictive analytics, data mining, text analytics, and statistical analysis [61]–[63].

The authors in [64] provide various big data applications in smart cities, namely smart grid, smart health care, smart transportation and smart homes. TreSight [65] is an example smart city big data application that uses Big Data Analytics (BDA) and Internet of Things (IoT) to form a recommendation system that aims to improve the smart tourism in the city of Trento, Italy. Furthermore, the output of data analytics can assist decision making processes. Cities like Malaga, Amesterdam and Boston are well-known cases for applying BDA techniques to model the behavior of urban inhabitants. To cope with computing and storage limitations in handling crowdsensed big data, and improve data quality, the authors in [66] present the architectural design of cloud based big data analytics. Authors in [67]–[69] study the big data analytics using novel encryption algorithms —such as homomorphic encryption— to eliminate privacy concerns on medical data.

Integration of big data analytics and mobile crowd-sensing introduces mutual benefits to both domains as the authors in [70] consider mobile crowdsourcing applications to explore the big data concept, understand the semantic of business data and manage crowdsensed big data storage services. Recent studies [71]–[74] elaborate on a vast number of business opportunities that will arise from the IoT phenomena, combined with Big Data analytics. Scalability remains a crucial challenge in big data analysis; to address this issue, the authors in [75] introduce a context-aware computing platform and a traffic assistant application on top of it to automate the collection and aggregation of large scale contextual data. Tranquilien [76] and Snips [77] are real crowd-assisted applications that capture urban mobility patterns about users' daily habits, interactions and surroundings to organize the users' transportation activities and improve the urban services. ParticipAct [78] is a real world experiment that provides an architecture for analysis of large scale crowd-sensed data. ParticipAct provides big data post-processing facilities as multi-layered data views and the crowd-sensed data-sets are published for researchers. The incentive mechanism used in ParticipAct is a threshold-based technique which basically renews the leased plan upon completion of a specific number of sensing tasks.

As seen in the brief summary of big data-crowd-sensing studies, data trustworthiness in the presence of adversaries remains an open issue. In this paper, we present a new framework to increase the trustworthiness of crowdsensed big data. Indeed, location-based privacy of the participants has been raised as an important open issue in mobile crowd-sensing systems [79]–[81], we leave addressing user location privacy to the future extensions of this study.

B. Challenges

When compared to the IoT-based sensing where any connected device can provide sensing as a service, implementing sensor networks with stand alone sensors leads to higher deployment and maintenance costs [33], [82], limited computing and data storage capabilities [83]. On the other hand, unique characteristics of mobile crowd-sensing such as energy limitation of mobile devices [84], security of stored data [85], [86], quality of sensed data (e.g., accuracy and trustworthiness of users) lead to further challenges in comparison to the traditional mote-class sensor networks [46]. Particularly in location-based crowd-sensing systems, task allocation (i.e. user recruitment), task handling (i.e. queuing), task delegation and reputation maintenance are reported as the four main issues to be addressed before mobile crowd-sensing becomes widely adopted [87]. A grand challenge in mobile crowd-sensing is incentivizing the users since users are concerned about the aforementioned limitations, and hence tend not to share their resources through implicit recruitment. For these reasons, policies to foster user participation have been largely investigated in the literature [88], [89], along with surveys and reviews to design effective incentive mechanisms in mobile crowd-sensing [22], [25], [90]. As reported in [91], incentives can be either monetary or non-monetary. For example, as a non-monetary incentive, the study in [92], proposes incentivizing the participants through leveraging social ties between them and their connections.

Game theory is commonly used for user incentivization, while maximizing the benefits of the crowdsourcer in the presence of a central platform [93]–[95] and under the peer data exchange settings [96]. As an example of game theoretic incentivization, Shuyun Luo, et al. [97] formulate a Stackelberg game between the platform and users for different cases.

Among all incentive techniques, gamification has received limited attention so far when applied to mobile crowd-sensing [30], [98], [99]. Gamification is applied in non-gaming contexts by employing game mechanisms with the objective of motivating users in active participation [28]. Wu et al. [98] propose to use gamification to reward users proportionally to their contribution in determining best WiFi hotspots in an area. Ueyama et al. [30] advocate gamification for a generic framework to incentivize user contribution in participatory mobile crowd-sensing. In [99] the authors show that gamification or monetary reward techniques are not efficient enough for collecting high quality data. Indeed, the main objective of gamification is to increase the quantity of data. To overcome such issue, a voting mechanism is introduced. In crowdsourcing, use of gamification through badge awards is studied for a popular platform like Stack Overflow [29]. The objective is to analyze the impact of badges on user behavior, and gamification has been proved to significantly improve user motivation.

A rating system and a reward-based scheme is used to incentivize users in [100]. Users' reputation history is maintained in order to allocate higher rewards to the users through a reputation protocol. This approach leaves newly joining users vulnerable to being eliminated before they can build reputation. The authors in [101] introduce a Subgame Perfect Equilibrium (SPE) as a bidding function to make payments to the users more efficiently. Unlike previous studies leveraging only monetary-based incentives [101], [102], in this paper, both game theoretic monetary incentives and gamification methods are applied.

Primary motivation of most participants is to increase their utility, especially in terms of monetary achievements. This introduces vulnerabilities to the crowd-sensing platform in the presence of malicious users who try to deceive crowd-sensing platforms by providing false data [103]. Thus, data trustworthiness is a crucial concern in mobile crowd-sensing since the trustworthiness of the service is a key indicator of effectiveness of the mobile crowd-sensing system. To address this critical issue, the authors in [104] adapt a fuzzy system with the quality of data and user reputation to evaluate the reliability of the sensed data in social participatory sensing systems. In [105], the authors introduce a cheating-resilient mobile crowd-sensing system by introducing user credibility-driven recruitment along with theoretical analysis. To provide a solution for this problem, we use the sensed data by other users as a reference for comparison to ensure that the submitted data is genuine. In the proposed method, users with higher reputation and more badges have higher chance to participate in sensing tasks.

Since the evaluation of data reliability in MCS has received little attention so far, we propose a game theoretic approach to model the interactions between users. In this game, a voting phase is formulated to evaluate the quality of the crowd-sensed data.

Table I
NOTATION USED IN THE PAPER

NOTATION	DESCRIPTION
n	Number of participants in each
T_S	Set of tasks handled by the users in the set S
W_τ	Number of winners at t-th recruitment
$N_i(t)$	Number of assigned votes to user i at time t
w_j	Vote capacity of user-j
r_i	Submitted reading of user-i
Val_i	Task value of user-i
x_j^i	Actual vote of user-j for user-i
$R_i^{'}(t)$	Updated trustworthiness of user i at the end of $t_i + \delta$
λ_s	Measurement distance threshold
γ_r	Rewarding threshold
$S_r^{ij}(t)$	Similarity indicator of task readings of users-i and j at time-t
ρ_m	Malicious user probability
$\int$	Probability of negative votes for a malicious user
Δ_{ij}	Measurement distance between the values of sensing tasks of user-i and j
δ	Delay time between the 1st and 2nd phase
t_i	Submission time of task-i
$t_i + \delta$	Collaboration time
$\tau_{duration}$	Duration of t-th recruitment
V_i	Total vote capacity for user-i at the first phase
${p_i}^t$	Total Payment to user-i at t-th recruitment
v^R	Total values of the tasks in the platform
$R_i(t)$	Trustworthiness of user-i at the end of time-t
${c_i}^t$	Total sensing cost to user-i at t-th recruitment
"HI-award"	Category of users receiving a high reward
"LO-award"	Category of users receiving a low reward

III. System Model

The proposed framework consists of three phases: 1) user recruitment, 2) game theoretic collaborative decision making, 3) gamification-based rewarding badges to the users. The crowdsourcer/platform is responsible for matching users with tasks; our model considers $n > 1$ users to perform tasks during each assignment process. Fig. 1 illustrates the applied

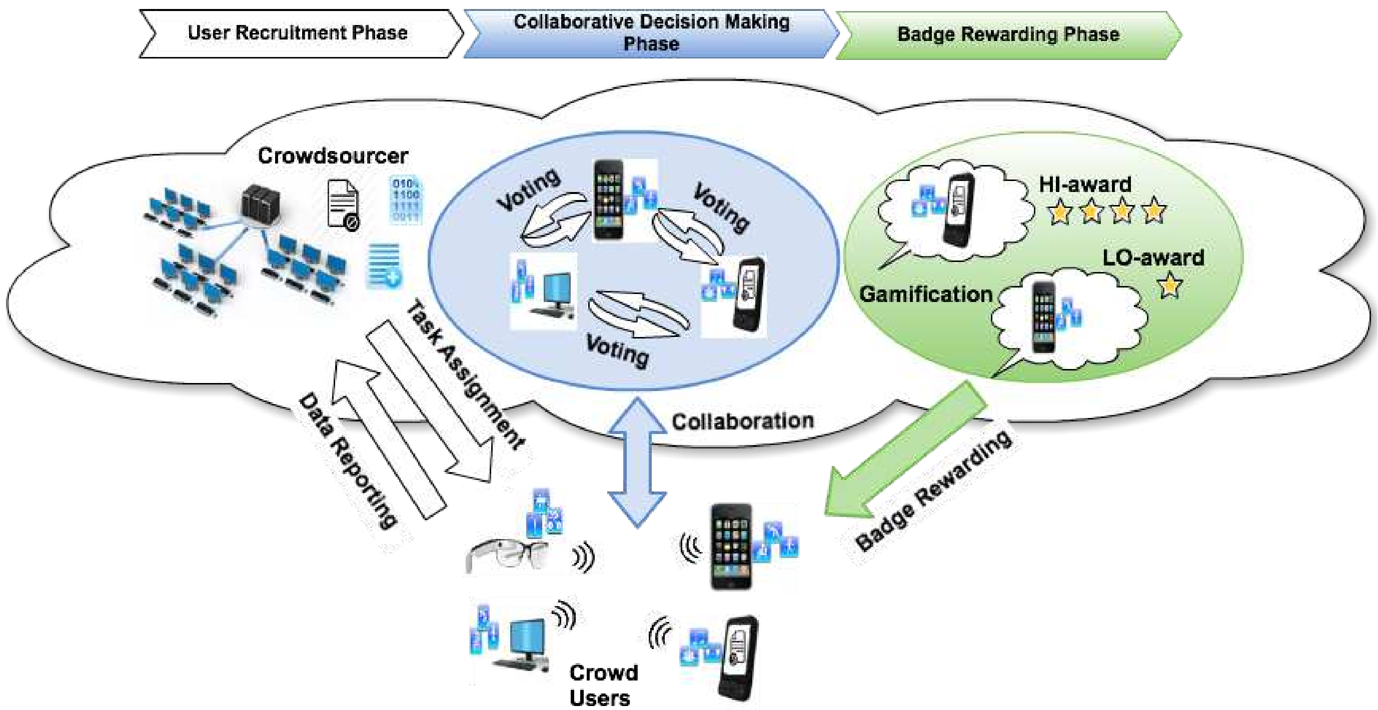


Figure 1. Proposed System Model. The crowdsourcer/platform recruits users and assigns them sensing tasks. Users collaborate in voting phase to ensure data trustworthiness and receive a reward upon providing useful feedback to the system.

algorithms in each phase and Table I lists the description of the symbols used in the following subsections.

A. Phase 1: User Recruitment

In this phase, users are recruited based on the following methods: Trustworthy Sensing for Crowd Management (TSCM) [34], which introduces statistical reputation-awareness to MSensing [106] and Social Network-Aided Trustworthiness Assurance (SONATA) [43]. SONATA adopts a recommendation-based Sybil detection approach for online social networks [107] to assess user reputations, thus, it is purely vote-based. Both of these schemes are based on a reverse auction procedure that consists of user selection and rewarding steps.

The proposed approach in this paper adopts only the user selection phase of either TSCM or SONATA. Selection between either TSCM or SONATA depends on the operation mode of the proposed framework, i.e., statistical or vote-based. TSCM calculates instantaneous user reputation based on true and false sensor readings. On the contrary, SONATA, determines instantaneous user reputations based on votes cast by other users that are sensing the same phenomenon.

User selection in TSCM, as well as in SONATA, is based on the winner selection step of MSensing [108], which is a user-centric reverse auction-based incentive mechanism. Participants join the auction by reporting their sensing costs (i.e., bids) as they are ensured that no user will be rewarded less than their bid in the auction. The recruitment is completed in two steps: winner selection and reward determination. MSensing aims at maximum platform and user utility and selects the winners based on their marginal contributions to the total value of the sensed tasks and their sensing costs, and sorts the users in descending order based on the marginal gain of the platform for recruiting each participant. This also copes with the situation where untruthful users aim to increase their income by bidding higher than the actual sensing costs. While selecting the users, TSCM and SONATA input user reputations in the marginal contribution function so that users with higher marginal contribution and higher reputation are more likely to be selected.

SONATA relies on user votes to ensure trustworthiness. In Eq. 1, w_j is the vote capacity of user i, x_j^i is the actual vote of user i and R_j is the trustworthiness of user j at time t.

$$R_i(t) = \frac{\sum_{j|c_{ij=1}} w_j x_j^i R_j(t)}{\sum_{j|c_{ij=1}} w_j R_j(t)} \tag{1}$$

In SONATA, the calculation of trustworthiness depends on the votes from the other users and the initial reputation. The vote-based user recruitment under the proposed scheme in this paper defines a *user reputation* based on the quality of submitted unlike SONATA where each user casts a negative or positive vote based on similarity score votes of the sensed data. In SONATA, each user casts a negative vote for a malicious user with a certain probability, $\int$.

While the vote capacity of a user in SONATA is increased/decreased by the positive/negative votes cast for the user, in our proposed method, the vote capacity of a user increases only if the user provides *useful data*. This is achieved by the collaborative decision making mechanism, which is defined in the next section. Given that n users are recruited at time t_i, all of the sensed data has to be sent to the platform by $t_i + \delta$, where δ is a specific offset time. At time $t_i + \delta$,

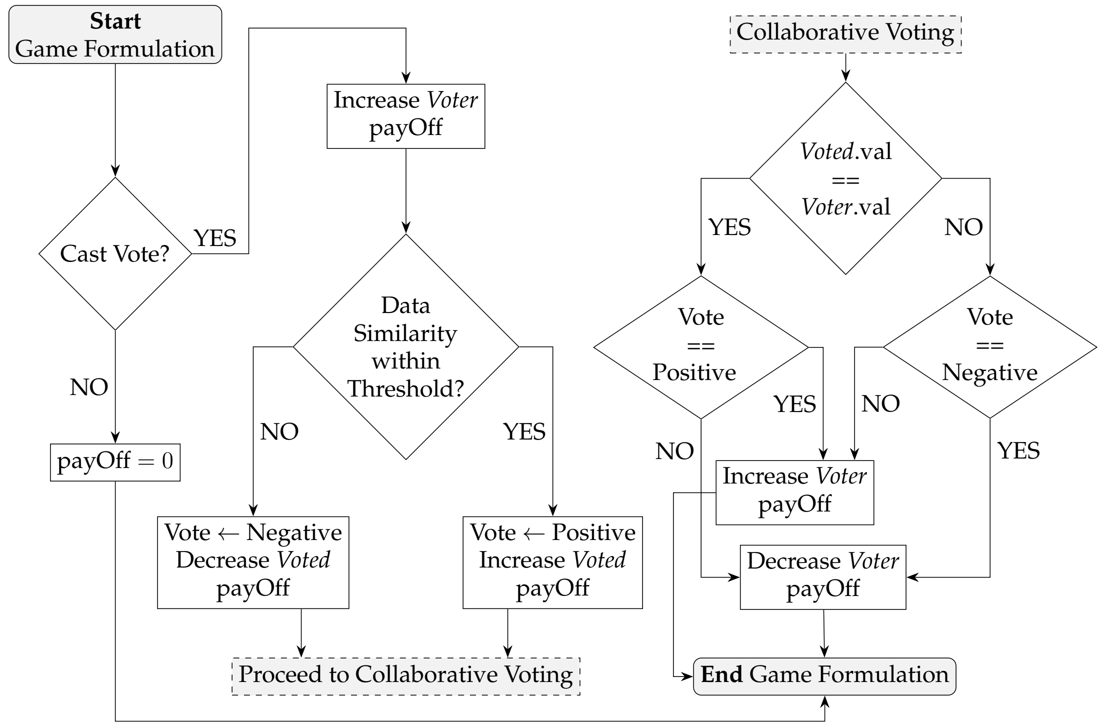


Figure 2. Collaborative decision making phase flowchart

all crowdsensed data is submitted to the platform, and all the participants are aware of the task values.

B. Phase 2: Collaborative Decision Making

Phase 2 and Phase 3 involve the payment method; users interact in a game and make decisions sequentially based on the submitted tasks. We formulate the problem as a Subgame Perfect Equilibrium (SPE), where players participate in a subset of a game and their strategy represents a Nash Equilibrium [109]. It is essential to assume that each player behaves rationally and independently in each subgame.

1) Game Formulation: We define a repeated subgame describing the users' strategy and each task is assigned to m users. The adopted strategies of a user are denoted by a tuple, $\{V, N\}$, where V denotes that the user is voting, and N denotes that the user is not voting. From a user's standpoint, participating in the voting phase is optional. The terms *Voter* and *Voted* denote a user casting a vote and the user receiving the vote, respectively. In case a user chooses to remain idle (i.e., not voting), (s)he obtains a payoff equal to zero.

When a user chooses to vote, the algorithm compares the measurement distance of both voter and voted data. Measurement distance is defined as follows. Let i and j be two smartphones each of which is equipped with multi-modal sensor array used in crowd-sensing campaigns. Given that r_i and r_j be two matrices of dimension $n \times 1$ denoting the sensor readings of users i and j at time t, respectively, the measurement distance between the two users at time t ($\Delta_{ij}(t)$) is calculated as shown in Eq. 2.

$$r_i = \begin{bmatrix} r_{i1} \\ r_{i2} \\ \cdots \\ r_{in} \end{bmatrix}, r_j = \begin{bmatrix} r_{j1} \\ r_{j2} \\ \cdots \\ r_{Jn} \end{bmatrix}, \Delta_{r_i, r_j}(t) = \sqrt{\sum_{k=1}^{n} (|r_{ik} - r_{jk}|)^2} \tag{2}$$

If the distance between two sensor measurements is below a certain threshold, λ_s, both users receive an increased payoff. Otherwise, the payoff of the voted decreases. A systematic presentation of the game formulation and collaborative decision making phases are illustrated in the flowchart in Fig. 2.

Determining vote reliability is at the last step of the game in order to ensure that truthful users receive higher ratings with respect to dishonest ones. This is achieved by having dishonest users lose credit upon casting untruthful votes. Consequently, upon increasing/decreasing their vote capacity, their reputation is directly impacted by Eq. 1 and, in turn, on their reward.

2) Collaborative Voting: The collaborative voting phase consists of two steps: i) Assessment of the quality of the contributed data, ii) Investigation of the accuracy of the assigned *Voted* user.

In step (i), the users compare the data to be judged with the data they own at time $t_i + \tau$. This is a sequential procedure; once the dissimilarity of the data reported/submitted by *Voter* and *Voted* is above a threshold λ_s, the *Voter* casts a negative vote. In the case of a negative vote, the platform increases the trustworthiness of the crowdsensed data. As a result, the voting capacity of the *Voter* casting truthful negative votes increases. On the contrary, when a *Voter* casts untruthful votes, the platform decreases its voting capacity.

In step (ii), the platform has knowledge of the value of the tasks, so it can judge whether the voters have provided genuine votes or not. Hence, the platform diminishes the vote capacity of users that cast misleading votes. This game among the users incentivizes users to collaborate for qualifying the value of sensed tasks; as users keep casting correct votes, their vote capacity keeps increasing.

The platform uses the following criteria to rate the participants: i) the value of the sensed data they submit, ii) trustworthiness of their votes. This rating is assigned according to the measurement distance between the readings of user i and j as formulated in Eq. 2. The calculated similarity indicator is used for badge rewarding. As formulated in Eq. 3, the binary similarity indicator between user i and user j at time t,($S_r^{ij}(t)$) indicates whether the data similarity criterion is satisfied.

$$S_r^{ij}(t) = \begin{cases} 1 & \text{if } \frac{\Delta_{ij}(t)}{\max\{|r_i|\}} \leq \lambda_s; \\ -1 & \text{if } \frac{\Delta_{ij}(t)}{\max\{|r_i|\}} > \lambda_s. \end{cases} \tag{3}$$

At the end of the collaborative voting phase, each user earns a total voting capacity, which is computed by taking into account positive and negative votes cast during each time slot as shown in Eq. 4, where $S_r^{ij}(t)$ is the similarity rating feedback that i receives from its neighbors.

$$V_i^{'}(t) = \frac{\sum_{j=1|j\in N_i(t)}^{|N_i(t)|} S_r^{ij}(t)}{N_i(t)}, \tag{4}$$

At the end of voting, the reputation $R_i^{'}(t)$ of each user is re-calculated by using the following two parameters: 1) the new collaborative vote capacity Eq. 5, and 2) the user's reputation $R_i(t)$ defined during recruitment phase Eq. 1.

$$R_i^{'}(t) = V_i^{'}(t) + R_i(t). \tag{5}$$

To obtain higher vote capacity, users are incentivized to provide correct feedback. The voting capacity is used in the badge rewarding step as the criteria for reward assignment. Thus, hostile and misleading feedback to the system never leads to awards.

C. Phase 3: Badge Rewarding

Incentive mechanisms typically focus on single user actions; on the contrary, gamification considers the overall user contribution [110], making it more beneficial when applied to long-term applications. In this paper, we employ a reward-based gamification method that awards badges to users that satisfy a certain reward level entry [29]. Distinguishing reliable/truthful users increases both platform and user utility. Therefore, the crowdsourcer tends to recruit users that contribute qualified data in a trustworthy fashion.

In [29], two reward allocation mechanisms are proposed: 1) absolute standard mechanism M_α, and 2) a relative standard mechanism M_ρ. The former issues badges when users provide a certain level of effort whereas the latter awards badges when users provide certain level of effort in comparison with the top contributor. The relative standard mechanism is more robust than the absolute mechanism because of being less susceptible to the particular conditions of the platform. We adopt the relative standard mechanism to select the winners of awards, which awards users with a badge when their vote capacity reaches a certain level.

In Phase 3, the users receiving a high reward are grouped in the "HI-award" class, while users receiving a low reward are grouped in the "LO-award" class (see Fig. 1). The platform uses the users' collaboratively computed vote capacity, in order to distinguish the users, which is formulated in Eq. 5.

$$R_i(t) = \begin{cases} R_i^{'}(t) & \text{if } V_i > \gamma_r, & \text{“HI-award”}; \\ R_i(t) & \text{if } V_i < \gamma_r, & \text{“LO-award”}. \end{cases} \tag{6}$$

Equation 6 shows that each user is paid at least as equal as its total cost. For users in "LO-award" class, their reputation does not increase from the value they have achieved in the user recruitment phase. While the members of the "HI-award" category increase their reputation and, consequently, they obtain a payment.

Table II
SIMULATION SETUP

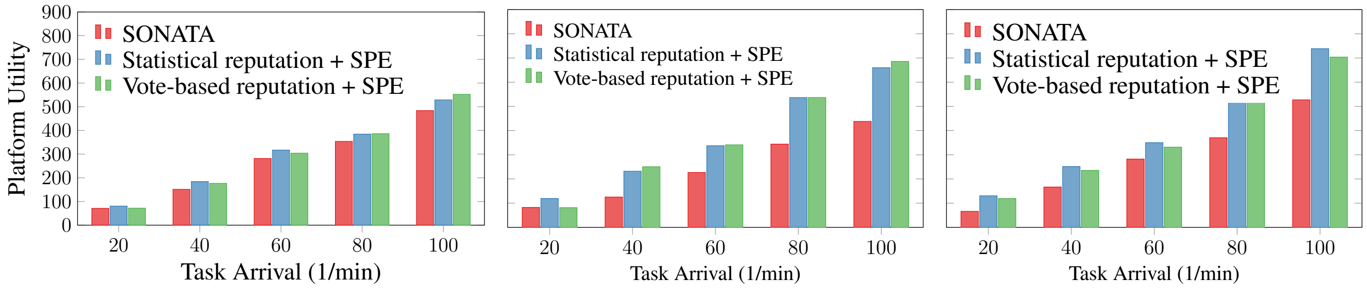
PARAMETER	VALUE
Terrain Size	$1000\,\text{m} \times 1000\,\text{m}$
Sensing Range	30 m
Number of Users	1000
Task Arrival Rates	$20; 40; 60; 80; 100/\text{min}$
Initial Reputation Probability	$0.5, 0.7, 0.9$
Malicious User Probability	0.05
Task Value	$\{1; 2; 3; 4; 5\}$
Measurement distance threshold λ_s	< 10 or 20 percent
Bid value	1; 2; ...; 10
Probability of detecting a malicious user in SONATA	0.20
Simulation duration	30 min

IV. PERFORMANCE EVALUATION

We simulate the proposed mechanism and compare the system performance of SPE-based user recruitment with the benchmark mechanism SONATA. The SPE-based user recruitment operates in two modes: i) vote-based (*vote-based reputation + SPE*), and ii) statistical reputation-based (*statistical reputation + SPE*) modes. The former adopts the user selection mechanism of SONATA [43] whereas the latter adopts the user selection phase of TSCM [34], which is a statistical reputation-based method.

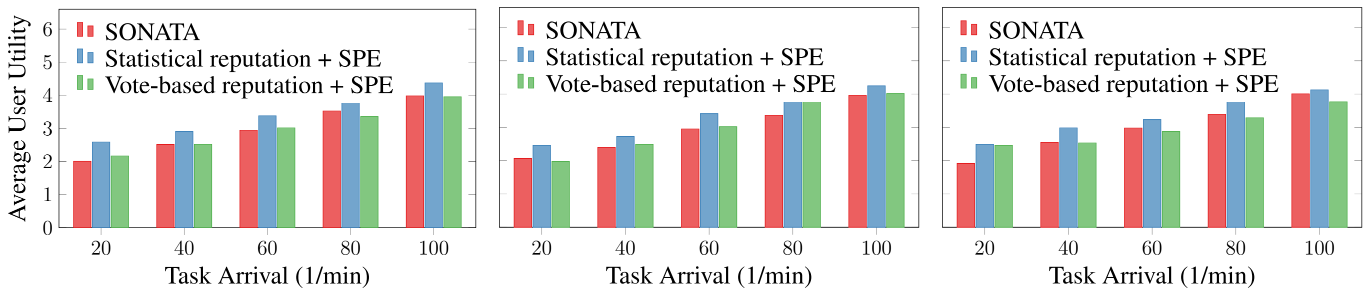
A. Simulation settings

Similar to [111], the simulation environment consists of a $1000\,\text{m} \times 1000\,\text{m}$ terrain. The number of participants varies between 100 to 1000 users. We assume three different scenarios with three different (50%, 70%, 90%) initial reputation of users in the monitored terrain. The malicious user probabilities is set to 5%. The duration of an event is set to 30 minutes and the platform assigns sensing tasks under various arrival rates, i.e. 20, 40, 60, 80, 100 tasks/min. The details of the simulation setup are presented in Table II. Three metrics assess the performance of the proposed framework:



(a) (b) (c)

Figure 3. Platform Utility vs. sensing task arrival rate. Figures are plotted for different percentages of malicious users: a) Malicious users ratio = 0.03, b) Malicious users ratio = 0.05, c) Malicious users ratio = 0.07.



(a) (b) (c)

Figure 4. Average User Utility vs. sensing task arrival rate. Figures are plotted for different percentages of malicious users: a) Malicious users ratio = 0.03, b) Malicious users ratio = 0.05, c) Malicious users ratio = 0.07.

1) *Platform utility*: Denotes the total received useful value from the participants deducted by the total payments awarded to the user as formulated in Eq. 7:

$$U_{platform} = \sum_{\tau} \left(v^R(W_\tau) - \sum_i {p_i}^\tau \right), \qquad (7)$$

where v^R is the total values of the tasks in the platform. Note that in both Eq. 7 and Eq. 8, ${p_i}^\tau$ is the total payment to the user i and ${c_i}^\tau$ is the sensing cost of user i during t. The parameter W_τ represents the number of winners during the auction period $\tau_{duration}$.

2) *Average user utility*: Denotes the difference between the payment received from the platform and the sensing cost. User utility is averaged by the total numbers of selected users in crowd-sensing, and the total number of sensing campaigns as shown in Eq. 8:

$$U_{user} = \frac{\sum_t ((\sum_i {p_i}^\tau - \sum_i {c_i}^\tau)/|W_\tau|)}{\tau_{duration}}. \qquad (8)$$

3) *Total amount of payment to malicious users*: Denotes the rewards made to malicious users. The objective of the platform is to minimize such value to improve the trustworthiness of contributed data.

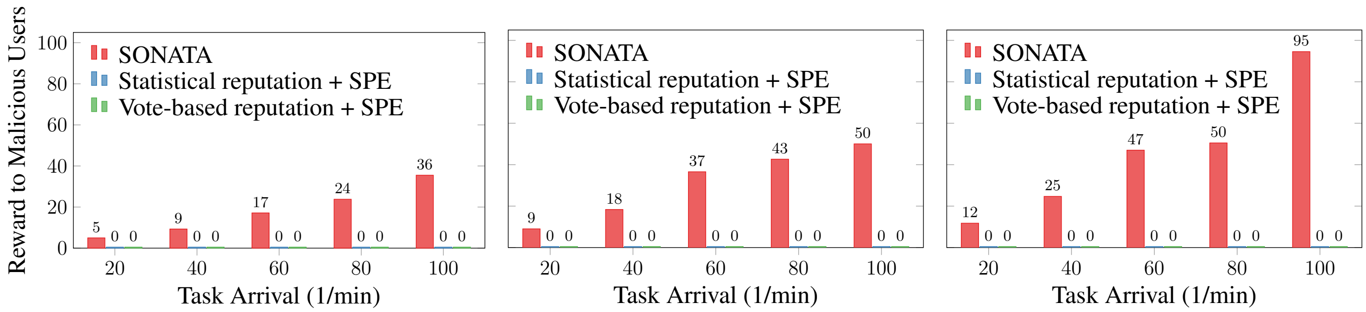
B. Simulation results

Figure 3 demonstrates the platform impact of different malicious user percentages in the terrain. As seen in Fig. 3, increasing the probability of malicious users leads to higher platform utility in all scenarios under SONATA and SPE-based user recruitment modes. The reason is two-fold: 1) statistical and vote-based reputation-aware modes of SPE are able to detect malicious users and reduce their payments, thereby leading to an increased platform utility, 2) by incentivizing users to provide useful data, the value of received data is higher in this framework.

At 5%–7% malicious user percentage, the maximum improvement over SONATA in terms of platform utility is as high as 55% under the reputation-based SPE recruitment. When the malicious population is set to 3% of the total crowd, platform utility is still expected to increase but not as high as the former two scenarios. As seen in the figure, the improvement is at most 13%.

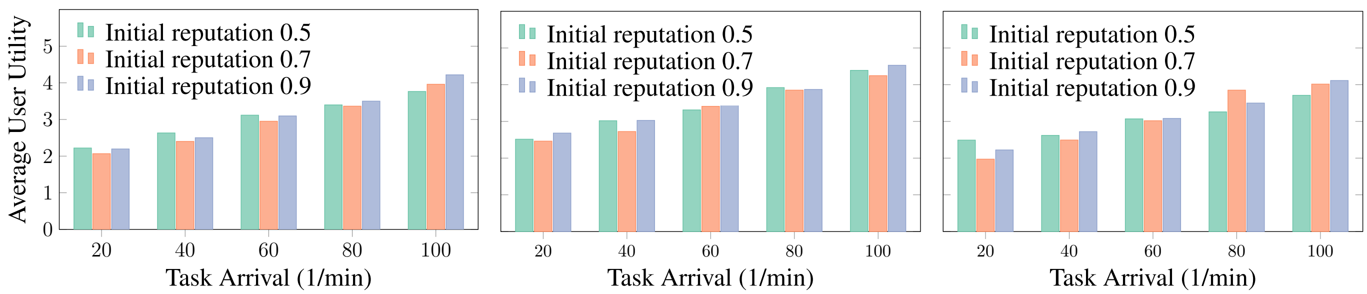
Figure 4 compares the three recruitment schemes in terms of average user utility. As expected, the degradation of user utility is not significant. The main reason lies in the fact that the platform pays more users with high number of badges. We observe that the statistical reputation-based method improves SONATA by an average of 15% and outperforms the vote-based SPE scheme. In the vote-based scheme, the users use more vote capacity than in the statistical reputation-based scheme during first voting phase. As a result, their sensing costs augment, diminishing the utility. Having defined the metric in function of both cost and income, to maximize user utility with fixed incomes, it is necessary to reduce the sensing cost.

Figure 5 illustrates the total payment rewarded to malicious users. The results clearly demonstrate significant improvements over the SPE-based user recruitment provides when compared



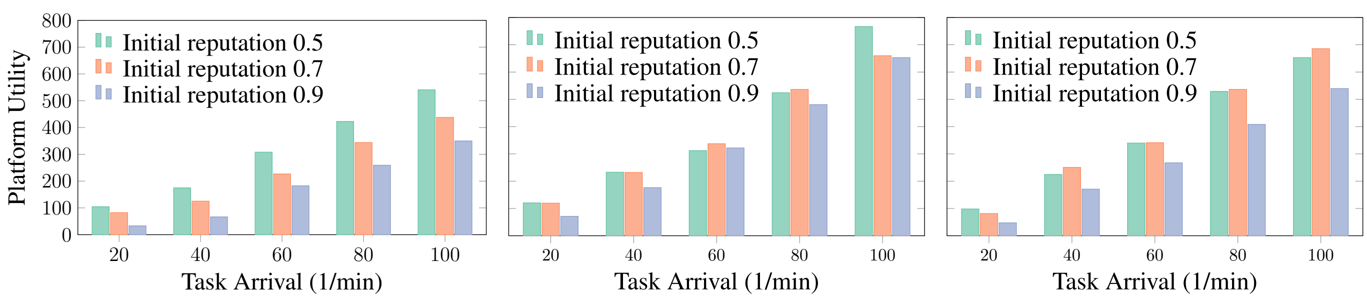
(a) (b) (c)

Figure 5. Reward to Malicious Users vs. sensing task arrival rate. Figures are plotted for different percentages of malicious users: a) Malicious users ratio = 0.03, b) Malicious users ratio = 0.05, c) Malicious users ratio = 0.07.



(a) (b) (c)

Figure 6. Average User Utility vs.Sensing Task Arrival Rate. Figures are plotted for different percentage of initial reputation: a) SONATA , b) Statistical reputation + SPE, c) Vote-based reputation + SPE.



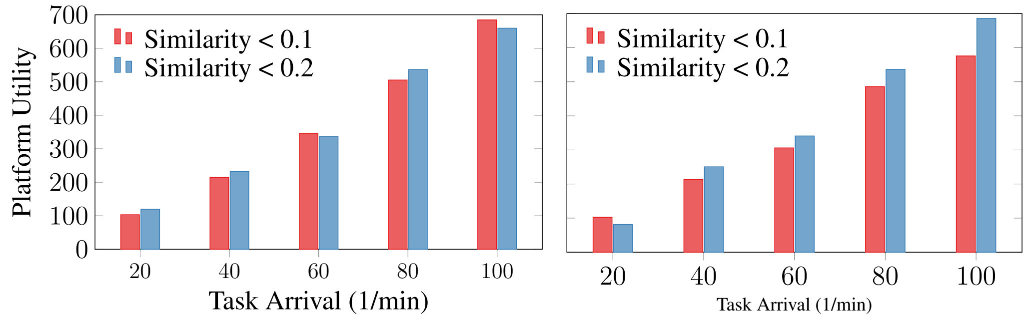
(a) (b) (c)

Figure 7. Platform Utility vs. Sensing Task Arrival Rate. Figures are plotted for different percentage of initial reputation: a) SONATA , b) Statistical reputation + SPE, c) Vote-based reputation + SPE.

to state-of-the art solutions like SONATA. The latter method falsely rewards malicious users while SPE-based techniques do not reward them at all. In SONATA, the malicious users providing fake data and decreasing system trustworthiness are assumed to aim to build bogus reputation; the adversaries achieve this by manipulating their sensing values to satisfy a predefined upper threshold. As a result, platform recognizes them as trustworthy users. The platform continues to pay the malicious users until their reputation reaches a lower threshold where the adversary behavior is identified, and does not reward these users any longer. In the proposed framework, SPE-based techniques use badges to identify user trustworthiness and the platform only rewards trusted users to improve both user and platform utilities.

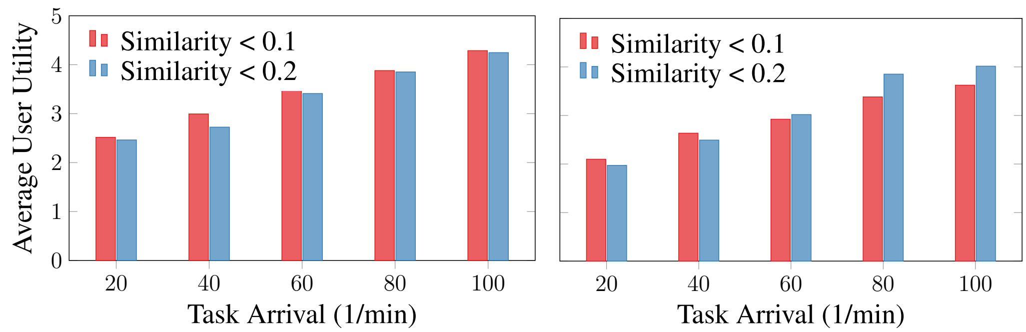
Figure 6 illustrates the average user utility when the initial reputation varies between 50% and 90%. Having 90% initial reputation results in the highest user utility especially in statistical reputation+SPE whereas designation of 70% initial reputation does not significantly improve user utility. This is an expected phenomenon due to the following reason: Setting the initial reputation to a high value will let the system start with rewarding more users. On the other hand, as the users in malicious behavior will be identified in time, the difference between various cases in terms of user utility is not significant.

Meanwhile the platform achieves the highest utility when the initial reputation is 50% as seen in Fig. 7. This is due to the platform's making conservative assumption instead of aggressively recruiting many users. This phemenon is more



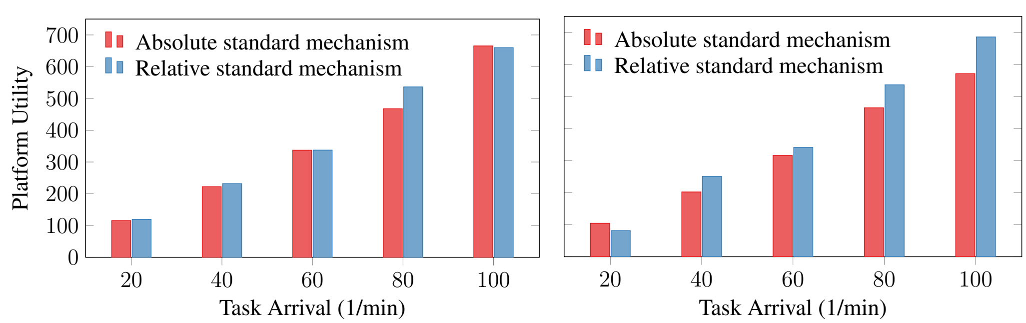
(a) (b)

Figure 8. Platform Utility vs.Sensing Task Arrival Rate. Figures are plotted for two methods of game theoretic: a) Statistical reputation +SPE , b) Vote-based reputation +SPE.



(a) (b)

Figure 9. Average User Utility vs.Sensing Task Arrival Rate. Figures are plotted for two methods of game theoretic: a) Statistical reputation +SPE , b) Vote-based reputation +SPE.



(a) (b)

Figure 10. Platform Utility vs.Sensing Task Arrival Rate. Figures are plotted for two methods of game theoretic: a) Statistical reputation +SPE , b) Vote-based reputation +SPE .

obvious under SPE+statistical reputation-based recruitment as users build reputation based on their readings but not on other users' recommendations and votes. Thus, it takes longer time for the users to build reputation by cooperating with the platform, which in turn increases the platform utility.

Figure 8 and Figure 9 illustrate applying different dissimilarity thresholds on the development of platform and user utility under the proposed SPE-based recruitment. Improving the quality of sensed data is one of the main contributions of this paper so the percentage of similarity between collected data sets significantly affects the performance metrics. To provide high quality data, two similarity threshold values are chosen. The first threshold enforces the dissimilarity between the collected data by the voter and voted to be less than 10% whereas the second one enforces dissimilarity less than 20%. Considering an dissimilarity threshold with higher range is not rational as the aggregated data may vary significantly. In vote-based reputation + SPE-based recruitment, by considering a wider range of dissimilarity spectrum leads to higher user and platform utility while in the case of statistical reputation + SPE-based recruitment, both thresholds of dissimilarity percentage introduce almost the same performance in user and platform utility.

Figure 10 and Figure 11 compare the impact of absolute

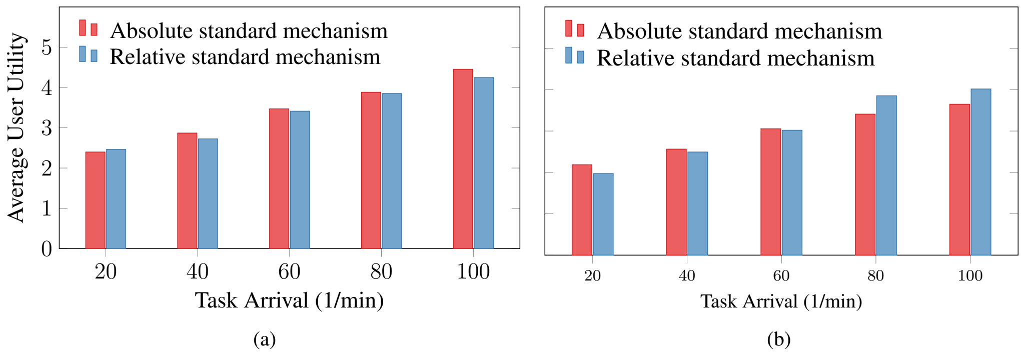


Figure 11. Average User Utility vs.Sensing Task Arrival Rate. Figures are plotted for two methods of game theoretic: a) Statistical reputation +SPE , b) Vote-based reputation +SPE .

standard badge rewarding mechanism and relative standard badge rewarding mechanism on user and platform utility under statistical reputation + SPE-based recruitment and vote-based reputation + SPE-based recruitment. The highest platform utility is achieved by applying the relative standard mechanism in both game-theoretic methods. This is because more users are recruited in relative standard mechanism and more accurate data is submitted to the platform (see Section III.C for detailed explanation on the two mechanisms). As for the user utility, as users are paid based on their announced costs, all participants who are recruited will receive payments; hence under both mechanisms, users will achieve almost the same utility.

V. Conclusion

Mobile crowd-sensing (MCS) has shown a great potential to make available sensing and computing of large volumes of data through smart phones, tablets and wearable technologies. Motivating users for sensing and reporting big data in a reliable manner is the key challenging issue for the success in MCS platforms. In this paper, we designed a gamification incentive framework to foster users participation in crowd-sensing and to ensure trustworthiness of sensed big data.

Our proposed framework adopts the winner selection mechanism from a previously proposed method, namely, Social Network-Aided Trustworthiness Assurance (SONATA) [43], and improves the rewarding step by integrating reputation of the users with the awarded badges. To receive badges, users collaborate to build their reputation through a voting system, derived from a repeated Subgame Perfect Equilibrium (SPE). Extensive simulations prove that SPE method is: 1) trustworthy, meaning that users provide useful data to achieve higher income, 2) profitable for users, meaning that not only each user is paid based on its true cost, but reliable users receive higher payments. Moreover, based on simulation results, the proposed SPE method prevents completely the platform to pay to malicious users, i.e., their reward is zero. Meanwhile MCS opens up a wealth of concerns about the involvement of users and the accuracy and reliability of produced data. Clearly, as shown in our proposed method, real time big data analytics is required to take advantage of provided reliable data to make comprehensive models of sensed events.

We are currently investigating the real-time cases of MCSs where delay sensitive crowd-sensing tasks are assigned to mobile users. Furthermore, we are extending the proposed framework incorporating other trustworthiness features such as mobility and residual power levels of participating devices, as well as context awareness in crowd-sensing applications.

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