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Monetary Incentives in Participatory Sensing using Multi-Attributive Auctions

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Participation of people is the most important factor in providing high quality of service in participatory sensing applications. In this paper we study monetary incentives in order to stimulate user's participation, especially in applications that rely on real-time data. Providing such incentives is hard because the service provider cannot determine the price at which each user would be willing to sell his own sensing data. Introducing traditional reverse auction mechanisms would allow to reveal this value, but they do not take under consideration the fact that sensing data are not all of same quality. This paper applies Multi-attributive Auction mechanisms that besides negotiation on the price, help service providers select the sensing data of the highest quality and also give users the incentive to further improve on them. We verify the benefits of this scheme using simulation experiments and we identify further research challenges.

Keywords: participatory sensing; monetary incentives; sensing data; multi-attributive actions; privacy

1. Introduction

The wide adoption of mobile devices in combination with the spread of the Web 2.0 paradigm on the Web recently created the right conditions for a new scope of research, often referred to as mobile phone sensing [1] or participatory sensing [2]. It complements our previous efforts in wireless sensor networks and due to sensor-rich devices, geo-localized user-generated content can now be created any time and anywhere. Other sensors, besides geo-location chips, such as camera, gyroscope, light sensor or accelerometer started to become more and more prevalent in mobile devices carried by billions of people, enabling new large-scale practices.

Currently researchers experiment with these new possibilities enabled by the sensing capabilities of mobile devices. As a consequence, today's suggested participatory sensing projects are not restricted to a few fixed services, but rather appear as a broad set of different, dynamic, and feature-rich services that are both exciting and helpful to citizens [1]. Some of these services are personalized, for instance computing people's daily exposure to pollution [3], keeping track of their dietary habits [4], etc.

But the most interesting projects are those that share the vision of a sensor data-sharing infrastructure, where people and their mobile devices provide their

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collected data streams in accessible ways to third parties interested in integrating and remixing the data for a specific purpose/campaign. A popular example is a noise mapping application, which generates a collective noise map by aggregating measurements collected from the mobile phones of volunteers [5–7]. It can raise citizen awareness of noise pollution levels, and aid in the development of mitigation strategies to cope with the adverse effects. In similar applications, people monitor air pollution [8] or road and traffic conditions [9].

A key factor for the success of such applications lies in the people's participation in data sensing activities. Even though the ubiquity of mobile devices makes mass participation feasible, as attempted in [10], it remains questionable how the general public can be motivated to participate. Participatory sensing projects, so far, call users to volunteer and offer the sensing capabilities of their mobile devices without getting or perceiving any immediate benefits. These attempts have only been moderately successful and make it clear that the focus of research should be extended to investigate what kind of incentives would make people get involved more actively in such projects.

From the viewpoint of service providers that collect and utilize sensing data, monetary incentives could increase user participation for the service. It could help service providers attract a large number of participants and thereby increase not only the collected amount of data, but also its quality, in order to offer a higher quality of service back to the users.

In the case of offering monetary incentives, a challenge for the service provider is to determine the price that users expect for their effort of collecting and submitting the data. This price may depend on the individual preferences of the users and how they perceive the cost of participating in the process. Sensing takes time, interrupts other activities, consumes additional battery power and data traffic bandwidth, and most importantly may require users to give up some of their privacy. Indeed, shared sensing data becomes intimately related to the personal sphere of the individual and a lot of personal information could be revealed as a by-product of the process [11].

This means that each user has his own valuation and thereby a minimum price that he expects to receive, depending on how much effort and personal information he has to give, in order to collect and provide sensing data for a service provider. This valuation naturally differs among individuals and based on the context or situation they are currently in. So, users offer to harvest the heterogeneous resource "sensing data" at an individual and prior unknown minimum price.

Our contribution

In this paper, we introduce multi-attributive auctions (MAA) as a dynamic pricing scheme for participatory sensing. We argue that this mechanism provides benefits attractive for participatory sensing and in particular:

(i) Service providers can avoid the challenge of determining the price a user expects to receive for his sensing data.
(ii) Service providers can influence the data quality of the sensing data through the auction process, in order to meet their application requirements.
(iii) Users are able to evaluate and improve on their data quality during the auction process, in order to archive a higher bid.

Multi-attributive auctions have been typically applied so far in business-to-business procurement cases. However, to the best of our knowledge, it has never been applied in cases where simple users are involved in the bidding process. By doing so, we have a completely new setting of roles, where simple users are the sellers and the service provider is the buyer of a virtual good "sensing data". This allows us to address the complex nature of incentives, compared to the limitations of "classical" pricing mechanisms and achieve at the end higher utility. In this paper, we especially emphasise on privacy and usability considerations of such mechanisms and discuss how MAAs can be incorporated in participation sensing systems, such that these dimensions are also enabled.

The rest of the paper is structured as follows. In the next section, we discuss existing incentive mechanisms in participatory sensing and in Section 3, we argue what requirements such mechanisms should satisfy. In Section 4, we argue why multi-attributive auctions are the appropriate pricing mechanism for participatory sensing. Then, in Section 5, we present the attributes that we consider important to be included in the corresponding utility function, specifically for the participatory sensing paradigm. Section 6 builds the overall communication model that is appropriate to incorporate MAAs. The simulation experiments in Section 7 demonstrate the benefits of using MAAs for sensing data, compared to the next best choice, i.e., reverse auctions. Finally, in Section 8, we discuss future research directions and we conclude the paper.

2. Incentives for Participatory Sensing

In this paper we focus on sensing projects that target the community level and in which users sharing commons do not necessarily get a self-reflecting benefit from offering their sensing capabilities. As in many community-based services, a key factor in participatory sensing lies in the leverage of participation in data gathering. Even though the ubiquity of mobile phones makes mass participation feasible, it remains questionable how the general public can be motivated to voluntary participate.

There is some recent work that studies the problem of incentives for participatory sensing. Broadly speaking, we could identify two research directions. The first one studies incentives, which are not monetary, but they are rather based on mechanisms of social networks and on-line communities to make participants and their sensing activities visible to one another [12, 13]. In this way users are able to receive recognition for their contributions, build up a reputation and receive attention. In the similar direction, some related work investigates enhancing motivation through gaming [14].

The second direction concerns monetary incentives, which is also the approach taken in this paper. From the user's point of view, Reddy et al. [15] showed in user trials that a set of micro-payments was effective in encouraging participation throughout a data collection task. They experimented with fixed prices and concluded that having a fair micro-payment (20 or 50 cents per valid submission) with an achievable maximum pay-out is a good strategy to have a balanced participation of users. In this regard, micro-payments constitute very strong means to influence users in favor of a service provider. However, in practice, micro-payments typically are given out in form of coupons rather than pure micro-payments. The advantage of this approach from a service provider's point-of-view is that a significant amount of these payments is refunded by the Point-of-Sales issuing these coupons in order to advertise for their products. However, the drawback of coupons is that they can only be used for a certain purpose - and not universally, like money earned from micro-payments.

Service providers offering fixed prices for the acquisition of sensing data cannot address the diversity of the resource "sensing data". As discussed in the previous section, the price that users expects to receive for their efforts is different among individuals and depends on many parameters. So, a better alternative for a pricing scheme would be a traditional auction (e.g. English auction) that can help to reveal the expected, unknown price of a user for his contribution.

Lee and Hoh [16] proposed recently the use of Reverse Auction based Dynamic Price (RADP) as a pricing mechanism in participatory sensing. Users bid for selling their sensing data, the service provider selects a predefined number of users with the lowest bid and the winners receive their bid prices for the data. In order to maintain the desired number of participants, the mechanism is adapted to prevent those who lost the auction to drop out. For that reason, in the next round, the losers of the previous one are given increased winning probability by virtually decreasing their bid price at the service provider.

However, this is a sub-optimal solution, because a user's auction bid would consist only of the price a user expects to receive for his sensing data and does not allow to negotiate on the data quality as well. Here we need to take under consideration that sensing data are not all of same quality. In order for a service provider to provide a better service, collecting data of high quality is important. For example, better location precision or higher sampling frequency are factors that are of interest to the service provider. Negotiating on the price alone does not provide any control over the quality of the collected data and therefore does not help service providers meet their application and quality of service requirements. This paper shows that in the paradigm of participatory sensing, MAAs are an attractive solution to help service providers select the most suitable sensing data, but also provide users with the incentive to improve on them.

An alternative approach would be to select beforehand those participants that are most probable to submit high quality data for a given application (or campaign) and then recruit them by offering a micro-payment, as suggested by Reddy et al. [17]. The evaluation is based on past experience from the interaction with participants, i.e., how well they performed in previous campaigns, as well as continuous monitoring of their current mobility patterns, in order to approach those participants who will offer the best coverage of the targeted area.

Besides the obvious privacy concerns that this approach raises, it does not directly motivate people to improve on their data, since they are already pre-selected. In the approach suggested by this paper, the evaluation of the data collection performance and availability takes place on the fly and locally on the mobile phone of the user, by embedding the performance parameters inside the price calculation function and dynamically re-calculating the price when these parameters change. As everything happens locally on the mobile phone, privacy considerations can be addressed more easily.

3. Requirements for Incentive Mechanisms

It already starts becoming apparent from our discussion above, that incentive mechanisms can become the key-factor to the success of participatory sensing campaigns, as they can motivate people to participate with reporting sensing data. But this is hardly enough. Service Providers need to be able to offer a certain Quality of Service based on the collected data, so giving out incentives should result in a corresponding quality of data that they can use to provide a service according to the needs of their data consumers. So the question becomes, which data quality parameters affect the willingness of Service Provider to offer incentives?

These parameters relate to the quality of the sensed data, directly or indirectly. This is apparent in the work of Buchholz et al. [18], where they argue that the quality of data depends not only on the precision or resolution of the provided data (in our case, sensed data) but also on indirect factors, like its trustworthiness. In addition, Leh and Hoh [16] elaborate on the importance of an incentive mechanism to be able to retain existing participants, as well as provide location privacy. We show below that these parameters also indirectly affect the quality of the sensed data at the Service Provider. So, overall, we come down to the following list of requirements:

- *R1 - Quality of reported sensed data.* Depending on the application, collected data should be of certain quality level, affected by technical parameters, like the overall sensing time, the location accuracy and distance from a targeted area, the sampling frequency, etc. Improving on these parameters increases the data quality on one hand, but on the other hand, it also increases the energy consumption on the mobile device or requires some additional effort from the participants. Quality of data is also affected by other parameters, like sensor precision or localization capabilities (e.g. GPS or cell-based), but they are usually fixed characteristics that mobile users cannot improve on.
- *R2 - Trustworthiness.* Trustworthiness describes how likely it is that the provided sensed data is correct. The very openness that allows anyone to contribute data also exposes the applications to erroneous and malicious contributions. People can get involved with the sensing process and therefore manipulate the output. For example, one could shout close to the microphone, when sampling the noise level. This is currently an open problem, and only a few suggestions exist on how to solve it. One way is to build a reputation system that allows the server to associate a reputation score with each contributing user that reflects the level of trust perceived by the application server about the data uploaded by that device over a period of time [19]. Incentive mechanisms should incorporate methods developed to deal with this problem. For example, in the case of monetary incentives, the service provider could pay more to well-known and trustworthy users, compared to new users or anonymous users. Similarly, in case of non-monetary incentives, one could publish this reputation score to the community, so that people are motivated to improve on it [12].
- *R3 - Retaining participants.* In the case of monetary incentives based on auctions, users compete with each other and therefore some of them will lose the auction. It is important that these users get an extra incentive to return and participate again, so that the user-base is not decreased. Whereas new participants naturally increase competition for selling sensed data, existing participants may have already gained a reputation and established their trustworthiness. Therefore they are more valuable to a service provider than new participants.
- *R4 - Location Privacy.* Location privacy can indirectly affect the quality of sensed data. Over the last years there is an increasing public awareness of privacy and several research studies present convincing data that privacy concerns have an impact on people's acceptability and adoption of new technologies [20, 21]. Given that user's location information is attached to the sensing data reported by mobile phones, location privacy becomes a main concern, and incentive mechanisms should consider it. On one hand, service providers are willing to give more incentives for more accurate information, while on the other hand users need to withhold information in order to protect their location privacy (e.g. by reducing the precision of the location). Incentive mechanisms should be able to accommodate this trade-off and enable people to keep control over their own privacy.

The above requirements influence the design of incentive mechanisms, and in the following sections we will show how a mechanism based on MAAs can address them. But even if an intensive mechanism is designed correctly, there are still side-parameters that can affect the willingness of mobile users to participate. We identify here two of such parameters: usability and transparency. Whereas usability is a prerequisite for people to use a service [22], transparency lays the foundation for a user's trust in such a service [23]. Even though these parameters do not directly influence the design of the incentive mechanism, caution must be taken that the integration of the mechanism to the overall participatory sensing system preserves these properties. Failing to do so, could cancel out the goals of incentive mechanisms and have the opposite result of discouraging people from participating.

- *Usability.* Since incentive mechanisms target to stimulate the participation of the users, the interaction with them is an important part. What we consider important factors are the user interface and the degree at which users are required to be involved. Options could range from daily contribution summaries to *in situ* reminders. Reddy et al. report some results from the evaluation of user trials, where some people even expressed the desire to have a map interface showing the targeted area or an augmented reality browser to help discover nearby locations for participation [17]. But what is important to pose as a requirement is that the user interface on the mobile phone should not be intrusive and instead allow users to be involved in the process at the degree they define.
- *User control and transparency.* The optimum of user participation can be achieved by maximising incentives and minimizing user workload through effective interfaces. However, simply minimizing workload by keeping information flows hidden is clearly not a viable option for creating a trustworthy system, as this conflicts with the need of providing transparency to the users on which of their personal information is flowing to third parties and when. Addressing this trade-off should be considered by participatory sensing systems.

So, offering incentives to users requires the consideration of multiple parameters, but at the same time it presents an opportunity to improve the experience of participatory sensing overall. In this paper we concentrate on monetary incentive and we investigate pricing mechanisms that can accommodate this complexity. In the following section, we elaborate on the disadvantages of "classical" pricing mechanisms and why the multi-attributive auction format can get us closer to our requirements.

4. Market-based Acquisition of Sensing Data

On one hand, sensing data considered as a resource imposes different procurement costs for individual users (e.g. for battery power or disclosed personal information). On the other hand, service providers as processors of this resource have individual requirements and considerations about its quality. Therefore, the question arises whether there is a pricing mechanism, which allows actively communicating this kind of information between the two parties, in order to determine a price that reflects the demands of both sides.

4.1 Determining a Pricing Mechanism for Sensing Data

Fixed pricing could be excluded from the list of appropriate pricing mechanisms for participatory sensing, due to the information asymmetry between mobile users and service providers. So, for a service provider in order to reveal an individual user's monetary expectation of an incentive in exchange for sensing data, interactive, dynamic pricing mechanisms have to be introduced [24, 25]. In this regard, the term "dynamic" denotes the fact that for the same good the price may be changed over time for its potential buyer; the term "interactive" means that the price for a good is determined within an interaction between buyer and seller.

Since the service provider (buyer) is the one who mainly determines the requirements of sensing data (i.e. data quality), we can exclude pricing mechanisms in which buyers and sellers are both directly involved in the price fixing process (e.g. price negotiations). Following Skiera et al. [24], the remaining dynamic and interactive pricing mechanism are two: *reverse pricing* and *auctions*.

For reverse pricing, the buyer proposes a price for the good, which is up for sale. If the proposed price lies above the secret price threshold of a seller, the buyer receives the good. In the other case, either a new bidding round begins or the buyer is not able to acquire the good [26, 27]. Even though reverse pricing schemes would be an interesting research direction for participatory sensing, they cannon incorporate the different qualities in the data that users submit, so we do not consider them in this work.

This leads us to auctions, in which buyers of a good submit monetary bids corresponding to their willingness-to-pay and the highest bidder receives the good. In this regard, two forms of auctions exist: Open-Cry and sealed auctions. For the former type, auction participants continuously and openly raise their bids in order to overbid the bids announced by their competitors. For the sealed auction type, each participant submits only one sealed bid (i.e. not known by competitors) and the auctioneer then selects the highest bid from all submitted bids at once.

Since the acquisition of sensing data from users has to occur in real-time, we need a fixed and immediate auction and winner determination. Therefore, we choose sealed auctions, which consist only of one bidding round. However, in order to finally consider such an auction-based pricing mechanism for sensing data, the traditional sealed auction format has to be further modified and aligned, as described in the following section.

4.2 Traditional Reverse Auction Format

In order to apply a traditional auction format (i.e. English auction) to the procurement of sensing data by service provider, the role of buyers and seller have to be reversed. Consequently, the service provider (buyer) now bids for offered sensing data by mobile users (seller) and thereby the auction format is called reverse auction. Moreover, during the auction, participants continuously decrease their bids until only one person with the lowest bid remains [28]. They win the auction round and consequently are able to sell the sensing data to the service provider at the price of their bid.

4.3 Multi-attributive Auction Format

A more sophisticated and complex form of a reverse auction format denotes the multi-attributive auction format. While reverse auctions allocate a good or resource only based on the negotiated price between seller and buyer, this special type of auction allows integrating additional attributes of a good into the auction bidding, besides the price. It originates from a procurement domain, in which a buyer expresses his preferences for a good in the form of a utility function [29]. For instance, it may depend on price and quality. Once all bids have been submitted, the seller, whose goods and other proposed conditions maximizes a buyer utility function, wins the auction [30]. Consequently, it allows the service provider (buyer) to communicate its quality requirements for a good and the mobile user (seller) is able to address these requirements alongside the submission of his monetary bid.

According to Bichler [28], the *utility function* represents the key characteristic or component of multi-attribute auctions. It reflects the overall value of a good for a buyer, based on its known attributes. That is, each bid comprises a monetary bid (i.e., the price that the user places), as well as a multiple quality dimension. Thereby, it can be represented as n-dimensional vector Q of either monetary or non-monetary relevant attributes. In the case of an additive utility function $S(x_j)$, the bid of a buyer can be expressed as $x = (x_1, \ldots, x_n)$. The seller evaluates each relevant attribute x_j through his utility function. As a result, the function $S : Q \to IR$ translates the value of each attribute into a *utility score*. At the end, the overall utility $S(x)$ for bid x constitutes the sum of all individual utility scores resulting from each attribute. If applicable, the individual utility scores can be weighted, with the weights $w_1, \ldots, w_n$ summing up to the value of one. The overall utility of bid is given by Equation 1.

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

For m submitted bids, a seller determines the winning bid, as given by Equation 2.

$$\max\{S(x_j)\}, \text{ where } 1 \leq j \leq m \ . \tag{2}$$

With the multi-attributive nature of sensing data and the quality requirements of service providers to be considered, MAA mechanisms become suitable for our scenario of collecting sensing data from mobile users. In the next section, we discuss what kind of attributes, x_j, could be considered for the utility function, before we incorporate the auction process in a participatory sensing architecture.

5. Assigning Attributes to Sensing Data

In the participatory sensing paradigm, the resource on which sellers (i.e., the mobile phone users) and buyer (i.e., the service provider) negotiate is the sensing data. The service provider defines a utility function $S(x)$ beforehand, including multiple attributes x_i that is important to him and on which users will compete to improve. Each attribute is weighted differently, by assigning the corresponding weight w_i. Since attributes with the highest weight have bigger impact on the utility function, users will try to improve those first. At the end, only the m users with the highest utility score win the auction.

Then, the question becomes: what are those attributes that the service provider can include in the utility function and challenge the users to improve? The obvious one is the selling price offered by the users, which the provider wants to keep low and within his available budget. The difference is, that opposed to reverse auctions, the service provider does not strive to minimize the expenses only, but also wants to satisfy several other requirements related to the data and the users, as we saw in Section 3. So, below we discuss a list of attributes, as an example of what can constitute the overall utility function (see also Figure 1), based on those requirements. We use the Quality of Context framework of Buchholz et al. [18] to derive a selection of such attributes for quality of sensing data. It is not meant to be a complete list, but only give an indication on what those attributes could be.

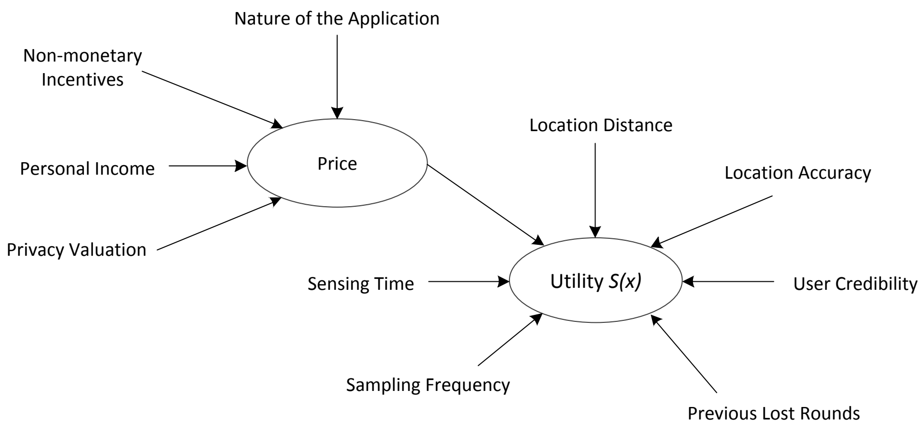

Figure 1. Parameters affecting the utility function, $S(x)$.

- *Price*: The price denotes the amount of money a mobile user demands for the provision of their sensing data. During the auction, the mobile user is able to decrease this price or bid respectively in order to improve his winning position relative to the other competing mobile users.
- *Amount of submitted data*: The sampling frequency and the overall time the sensors are measuring the environment affect the energy resources of the user's mobile phone. By increasing them, the user would devote more resources, but also increase his data quality and therefore his utility score.
- *Sensing location distance*: Service providers typically prefer a specific location, at which sensing data is to be collected by mobile users. In order to decrease the sensing location distance, a mobile user could decide to physical move closer to the targeted location. This improves the quality of the sensing data for the service provider and at the same time the value of the user's bid in the auction.
- *Location accuracy*: Blurring location data is a common technique to provide location privacy [31]. This however could reduce considerably the worth of the data for the service provider. The mobile user could be offered the possibility to reduce the blurring factor and provide more useful data in exchange for a higher probability to win the biding process.
- *User credibility*: Depending on the disclosed personal information of mobile users, a service provider is able to derive additional sensing data quality aspects. For instance, if an individual mobile user can be uniquely recognized by a service provider (e.g. based on a pseudonym) as opposed to anonymous users, the service provider has the opportunity to derive the creditability of the submitted sensing data, based on his reputation score and the available user transaction history.
- *Number of previously lost auction rounds*: Based on the transaction history of a mobile user, it can be revealed how many times they failed in winning prior auction rounds. The higher this count, the higher the utility score a mobile user gets in their current auction round (the actual score depends on the individual utility function of a service provider). In this way, we motivate users to keep participating even if they fail to win an auction from time to time. However, it needs to be transparent to the mobile users that they benefit from the fact they have previously failed to win an auction round.

After defining the above parameters of the utility function, we can now see why monetary incentive mechanisms based on MAAs can satisfy the requirements we defined in Section 3. Referring to Fig.1, the location distance, location accuracy, sampling frequency and sensing time are parameters that help us improve the quality of data, therefore satisfying requirement $R1$. The user credibility parameter directly corresponds to requirements $R2$, while the previous lost rounds is necessary for satisfying requirement $R3$. Finally, the location accuracy and sampling frequency parameter also serves as a way to address requirement $R4$.

Next, it is of particular interest to take a close look at the user's bidding price. What is important to the user and which are the factors that affect the price he requires? Below, we put together some of these factors.

- *Privacy Valuation*: The stricter the privacy attitude of a user, the higher the monetary incentive he expects in exchange for his sensing data, in case it reveals personal information. We elaborate further on this issue separately, in Section 6.2.
- *Personal monetary income*: The higher the monetary income and wealth of user, the higher a user expects to be rewarded for his sensing tasks. This is because the effort of a mobile user for collecting and submitting his data has to be rewarded in relation to his income or wealth [32].
- *Available non-monetary incentives*: Participatory sensing applications allow to introduce additional non-monetary incentives such as reputation of the mobile users [12]. The higher these incentives are valued by the users, the less the monetary incentives may be needed.
- *The nature of the application*: The goal of the specific participatory sensing application could address some sensitivities of the user, such as his position against pollution, etc. The sense that he contributes in a common goal for something that he cares about could be enough to participate, no matter how low the monetary incentives are.

Having concluded to the deployment of multi-attributive auctions in participatory sensing and discussed their composition in detail, we now move on to integrating this mechanism in such a system and show the communication steps that are required.

6. Integrating MAAs in Participatory Sensing

We assume that a service provider wants to provide real-time services, such as monitoring noise, temperature or CO_2 levels in an urban environment. In order to address the shortcomings of covering such a wide geographic area with dedicated sensor nodes, the provider takes the approach to collect the data from mobile phones of individuals. The idea, then, is to orchestrate the computing, communication, and sensing capabilities of a population of mobile phones, which happen to be at the area of interest or a nearby area, in order to enable large-scale sensing purely through software running on this existing hardware base. Each mobile phone transmits the sensing data from the environment to a central server through the mobile network. Then, the service provider aggregates the measurements from all users and processes them to deliver the service.

6.1 Communication Model

Broadly speaking, there are two communication models to collect sensing data from people, depending on the nature of the application [33]. In the first one, people are actively involved in the data collection process. Which data is important? How

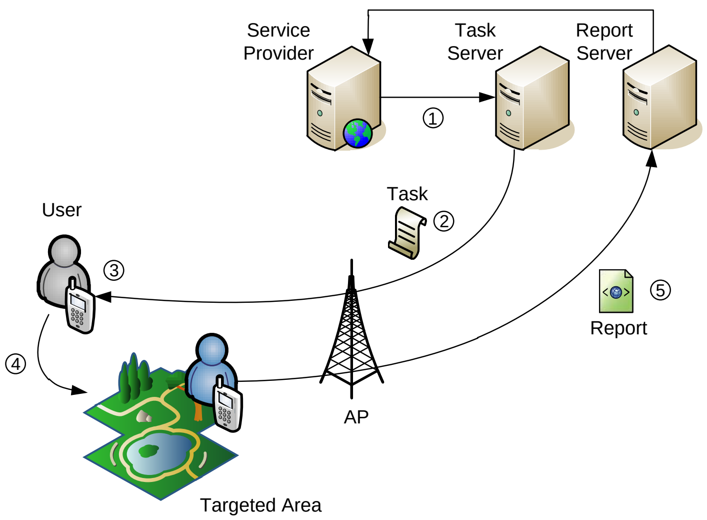

Figure 2. Communication steps in the acquisition process of sensing data.

much do we need? Humans can figure out how to collect public sensing data by making opportunistic choices on the spot. The second way would be to take a more proactive approach. That is, sensor sampling occurs whenever the state of the device (e.g. geographic location, available sensors, etc.) matches the application's requirements. In this case the device is remotely tasked to collect and report sensing data, utilizing in this way the device without its owner being actually aware of the sensing activity. In our example scenario, the service provider is the one who decides which data is needed and from which area. So the second approach, sometimes also called opportunistic sensing, is the most appropriate for our case.

However, the key question is how sensing tasks are distributed to the mobile phones. One option is to employ a *push* mechanism, as suggested by PRISM [34], where the participating nodes (i.e. mobile phones) register with the server and the server tracks the nodes and pushes only matching tasks to them, based on their context (e.g. location). For example, we may assign the task "measure temperature in area X" to Alice, when she is entering this area. This means that the system should monitor the current location of users, so that it knows which users are within the area of interest or are most likely to visit it; something that raises immediate privacy concerns. PRISM tries to limit this problem, by expiring registrations and requiring fresh registrations from time-to-time.

The second approach is to employ a *pull* approach, as suggested by AnonySense [35], where sensing tasks are posted on a server and the participating nodes download the tasks and match them to their context to decide which one to execute. This approach has the advantage that the nodes do not reveal anything about their context (including location) to the service provider, in order to receive the sensing task. At the network level, an anonymizing network, like Tor, is used to protect the network identity of the device. We adopt this approach here, since it offers a solid basis for privacy protection and enables users to decide on their own how much private information they want to give out, as part of the negotiation during the auctions.

Fig. 2 depicts the steps of the whole process and we explain them in more details in what follows.

Step 1: In order for the service to be real-time, the provider defines successive short time periods, within which sensing data are to be collected by people from a given geographic area. This is expressed by the service provider in the form of a task, which is submitted to a Task Server. The task contains two things: the *acceptance conditions* and the *utility function* $S(x)$. The acceptance conditions limit which mobile nodes may execute the task, e.g. it defines the required sensors, termination conditions, etc. The utility function incorporates the provider's budget and several parameters that affect the required data quality for the service provider, as explained in Section 4.3.

Step 2: The mobile devices of users, registered in the service, periodically check on the Task Server and choose tasks to run based on the acceptance conditions of these tasks. Additionally, some local conditions, defined by the users, can also be applied. Such a condition could be, for example, not to accept sensing tasks, if the remaining battery level is below a threshold.

Step 3: If the mobile phone accepts a task, users define their initial price, which is the first input in the attached utility function. In Section 5, we discussed several of the factors that could affect this price value. Besides the price, the quality attributes of the utility function $S(x)$ are also evaluated at this point, in order to produce the *utility score*.

Step 4: If not satisfied by the utility score, users are able to improve it, by acting on the data quality factors. For example, a user could choose not to blur the location information, or to move closer to the preferred sensing area of the service provider (as shown in Fig. 2).

Step 5: The utility score is recalculated and once the mobile user is satisfied with the value, he submits the characteristics of the sensing data to the Reporting Server for the auction round. The auction round begins at the end of each reporting time period and takes place between the users who have submitted their interest to participate in that round. Once the auction round winners have been determined, they submit the actual sensing data from their devices to the Reporting Server. Even though it is not shown in Figure 2, a Mix Network is also needed in Step 5, to serve as an anonymizing channel between the mobile phone and the Reporting Server and guarantee the privacy of the user at the network level.

6.2 Privacy Considerations of Users

The approach taken in this paper is that users should be free to decide how much private information they want to reveal to the service provider. Our system design is based on principles that hand this choice over to the user. At the same time, our utility function $S(x)$ embeds the natural tension between revealed information and privacy. Decreasing the privacy protection (e.g. revealing accurate location coordinates or attaching personal identifiers) the utility score increases, improving the chances to win the auction round. However, the attribute "price" in the utility function allows the user to increase the amount of money he demands, for giving out some of his privacy. We have reflected that in Fig. 1, but here we elaborate further, based on existing studies.

Chances are that users will indeed demand more money, if they reveal their privacy. There have been studies that try to identify how much privacy is worth for the users and assign a price to it [36–39]. Even though some of them present specific mean values, they all show that the distribution of privacy valuations from users is not centred around these values, but rather present big variance. Acquisti et al. actually showed more concretely, that privacy valuations are not normally distributed, but clustered around extreme focal values and that individuals may easily move from one extreme to the other, depending on contextual factors [38].

There are two interesting parameters that seem to affect the amount of money people require to reveal private information. The first one is how much they trust that their privacy is protected by default from the system. When they feel that their privacy is protected, people value it much more than when they feel their data may be revealed from the entity that collects it. The second parameter is the purpose for which their data is collected. Cvrcek et al. presented results from a cross-European study, where the median of the bids increased about twofold when compared to the bids when the data were to be used not only for academic purposes, but also for commercial purposes [37]. Here one has to take under consideration the cultural factors, as Brush et al. repeated the same experiment in the U.S. and did not observed a significant difference in the same question [39].

6.3 Usability Considerations

Throughout the paper, we have presented the auction as a process where the user is actively involved. As the auction takes place while the user is on the go, this raises concerns on usability of the application. In reality, we can minimize user's involvement, by introducing pre-configurations of the mobile client, such that the process can be automated according to user's preferences. There are no restrictions paused by the auction mechanism itself. For example, the client can automatically download and accept sensing tasks according to the user's location and energy remained on the mobile phone. Then the client can suggest a price, based on the user's profile and pre-defined ranges and eventually sense and submit the data. Ideally, the user could receive daily notifications at the end of the day, about the amount of money collected.

Alternatively, since multi-attributive auctions enable users to take actions to improve their data, it makes sense to notify them about that. For example, the user could receive a notification on his screen, stating his current utility score and suggestion on how to improve it (e.g. move closer to a specific area). Receiving such notifications could be turned on and off by the user, depending on the context.

6.4 Privacy User Interfaces

Privacy is a complex problem that is often hard to define [40], yet transparency and control clearly play a major role in its provision. The discussion on privacy and usability considerations above, bring to surface the well-known trade-off between the two. On one hand, if we target to improve usability of participatory sensing applications by allowing user to pre-configure privacy settings, capturing the large number of different contexts where sensing could actually take place would require a very complex configuration panel. On the other hand, allowing users to decide on the spot, every time a sensing report is sent, would decrease usability considerably. We identify this as an interesting open research challenge.

Designing user interfaces for giving people control over their own data is a cross cutting issue, involving many disciplines such as psychology, behavioural sciences, ethnography, formal (computer) languages, and of course user experience design. Of particular interest are individual privacy preferences (e.g., elicited through surveys about what data people are willing to share with others), privacy practices (e.g., observed during actual real-world interactions with services), and mental privacy models (e.g., for communication privacy policies). Iachello and Hong offer an in-depth overview of the vast literature in the area of privacy and human-computer interaction [41].

7. Simulation Experiments

Since the procurement of sensing data may involve the participation of many mobile users in real usage situations, in this section we perform several simulation experiments in order to demonstrate the general theoretical economic benefits of applying a multi-attributive auction format in such scenarios. With regard to further research, it is planned to conduct user trials based on the gained knowledge from the experiment, in order to see how these benefits translate into practice.

7.1 Simulation Model and Setup

In our experiments, we compare the traditional reverse auction format with the sealed multi-attributive auction format in order to demonstrate the benefits of the latter for both seller and buyers of sensing data. Therefore, our simulation model assumes one service provider as buyer of sensing data and a variable number of mobile users as sellers of the resource. The resource *sensing data* is described by the price and a number of quality attributes, as described by Eq. 1. For the sake of simplification we have assumed equal weights for all attributes. The values that these attributes receive would be defined by the actual users, but for the simulation experiment they were randomly generated based on uniform distribution, which is the most realistic assumption for multi-attributive auctions [28].

Based on the *Monte Carlo Simulation* model, 5000 auction rounds had been conducted for each simulation case below. Thereby, the presented diagrams reflect the corresponding results as average values from the conducted auction rounds.

7.2 Simulation Results

The first simulation experiment shows the utility outcome as a function of the number of negotiable attributes for a user. In particular, 50 users as sellers of sensing data and one service provider as buyer of the data were assumed. For simplicity, in this experiment we have assumed only one winner for the auction, and later on we examine the effect of having multiple winners separately.

The outcome is depicted in Fig. 3 and it demonstrates that it is beneficial for a service provider to allow users to negotiate on more than just one attribute (i.e. the price) during an auction. The reverse auction (RA), which allows users to negotiate only on the attribute *price*, provides the lowest utility for a service provider. In the case of a multi-attributive auction, where more attributes (e.g. location distance, privacy valuation and more) become negotiable, the utility of the auction outcome for the service provider increases monotonically. This increase of the utility score directly translates to an increase of the data quality.

The reason for this outcome is that negotiation on more than just one attribute automatically generates a greater variety of offers from users from which a service provider can choose, in order to maximize utility from buying off sensing data in accordance to his business objectives.

The second simulation case shows the change of the sensing data acquisition costs as a function of the available number of negotiable attributes by users. 50 users as sellers of sensing data and one service provider as buyer of the data were assumed. Again for simplicity, only one winner of the auction was assumed.

The results are shown in Fig. 4 and they demonstrate that the acquisition costs for service providers increase, once we apply MAAs and the price is no longer the only attribute to be negotiated. This is because users are no longer solely competing on the price for sensing being bought by the service provider. Competition is now

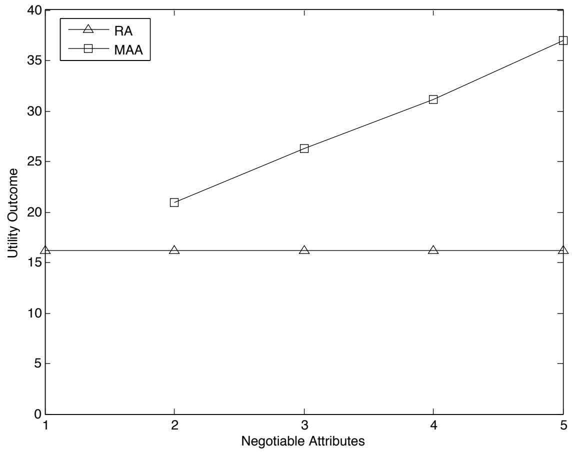

Figure 3. Utility outcome as a function of the negotiable attributes with users.

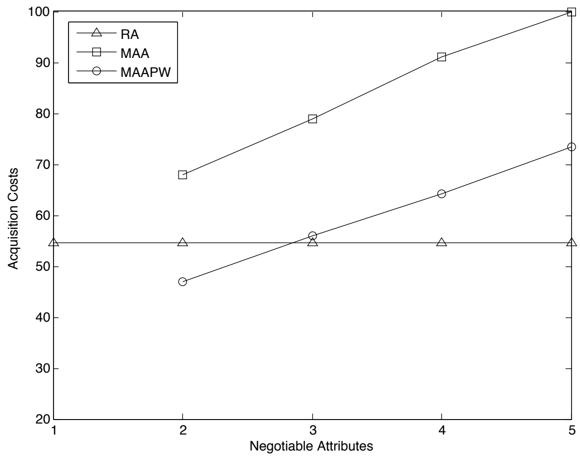

Figure 4. Acquisition costs as a function of the negotiable attributes with users.

equally distributed across multiple attributes on sensing data and therefore does not focus on price as the only attribute any longer. Whereas this might be quite intuitive, a service provider has the option to increase the weight for the attribute "price" within the utility function. This case is denoted as MAAPW in Fig. 4. Thereby, the service provider is able to reach a trade-off between acquisition costs and utility outcome based on the requirements of his application and business model. This means, the higher the weight on the price, the lower the acquisition costs and also the lower the overall utility outcome.

The next simulation case examines how the utility outcome changes depending on the number of participating users in an auction. It compares the RA with the MAA cases, assuming five negotiable attributes for the latter and one wining user. As shown in Fig. 5, the utility of reverse auctions and multi-attributive auctions increases with the number of users offering their sensing data, but not significantly. This means that MAAs *do not require a critical number of participants*, in order to be efficient. This makes them practical for any kind of applications based on sensing data.

In contrast to the previous experiments, Fig. 6 shows how the utility for service providers changes, if more than one user can win the auction. It is important to see the behaviour of the utility outcome in this case, as in participatory sensing we will require the data of several sources, in order to cover a geographical area efficiently. In particular, Fig. 6 shows two cases for MAA (for 200 and 1000 overall

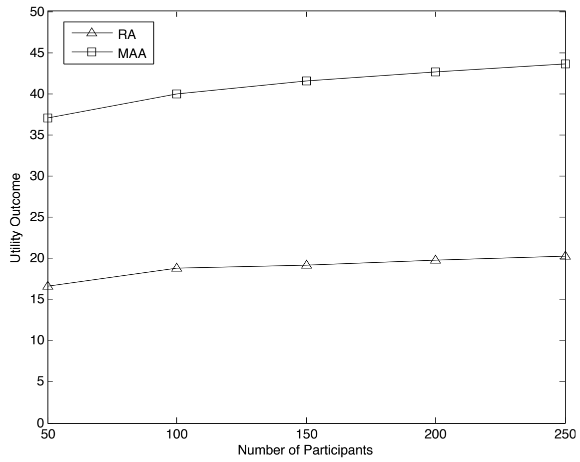

Figure 5. Utility dependence on the number of participating users.

participants), while the same is repeated for the RA case.

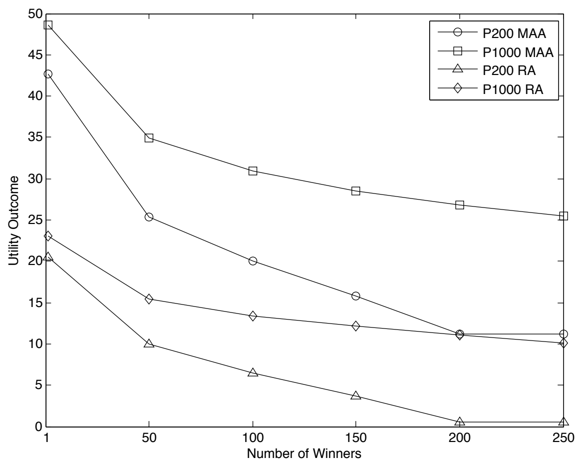

Figure 6. Utility dependence on the number of winning users.

This simulation case shows that an increasing number of winners leads to a decreasing overall utility for the acquired data. The reason for this lies in the fact that an increasing number of winning users also decreases the competition between the users. This ultimately leads to a lower utility. Consequently, a service provider has to carefully balance between its desired data quality (due to the amount of sensing users) and the desired overall utility of the collected sensing data. Nevertheless, it is important to emphasize that the MAA case still provides a higher overall utility than the RA.

7.3 Simulation Limitations

The simulation results in Fig. 3 indicate the opportunities for service providers to negotiate on sensing data quality while offering monetary incentives to users. The feasibility of measuring and influencing these parameters on mobile devices in the real setting is straightforward for most of them. For example, with the user moving closer to the target area, the distance is decreased. Similarly, local parameters like sensing time, location accuracy and sampling frequency can be extracted from the hardware settings of the mobile phone and the user can be given control over them.

Two special parameters deserve separate consideration, i.e., the user credibility and previous lost rounds. Both of these parameters are being computed on the service provider's side and as mentioned in Section 7.2, they cannot be manipulated (i.e. negotiated) by the user during the auction round. They only reflect user's behaviour as seen by the service provider. Here a suitable mechanism needs to be developed at the service provider's side in order to actually "measure" credibility. The same applies for the integration of the previously lost auction rounds.

In the simulation environment, all of the above parameters take random values according to a uniform distribution. Even though this cannot depict accurately the real setting, it is sufficient for our purpose to show the behaviour of the utility function. Experimental values would affect the exact shape of the graphs, but not the overall behaviour as observed in this paper. This behaviour is important to show the benefits of MAAs against other pricing mechanisms.

8. Conclusions and Future Directions

The application of multi-attributive auctions enables service providers to negotiate on the quality of sensing data in accordance to their needs, while at the same time users have the opportunity to evaluate the value of their current data quality and, if applicable, improve on their status.

We have conducted four simulation cases, in order to demonstrate that the MAA can actually provide benefits to service providers, by allowing them to acquire sensing data with a higher utility. The results show that the utility of the acquired sensing data can be increased with an increasing number of negotiable attributes. However, this higher utility comes at higher acquisition costs, which have to be considered by a service provider. Further, with an increasing number of participating users, also the utility of the acquired sensing data can be increased due to higher competition between users. On the opposite, with an increasing number of users required to win the auction (e.g. if multiple redundant data sources are required), the utility decreases, because of less competition between the users. However, the utility remains higher than that of the RA mechanism.

The conducted simulation studies in this paper give a reasoning for the benefits of applying multi-attributive auctions for the acquisition of sensing data, but several details of such pricing schemes comprise challenging research questions on their own. We identify here some of these open questions:

- *Service provider supporting specification of the utility function:* Critical to the success of multi-attributive auction formats is the specification of the service provider's utility function according to its business objectives. For instance, how can the distance of a user to the targeted sensing location be translated into the corresponding utility score and how does this function develop with increasing/decreasing distance? How can the attributes be weighted appropriately?
- *Decision support for users on how to formulate their auction bid:* Since users are no longer submitting solely a price as bid in a multi-attributive auction, formulating a bid becomes more complex. It will be important to reduce this complexity to the minimum, in order to foster the participation of users in sensing data and to support mobile users in placing a bid depending on their current situation. For instance, should a user reduce his expected price for submitting sensing data or should he physically move closer to the targeted geographic area in order to improve his chance to win the auction round?
- *User trials empirically evaluating the proposed multi-attributive auction format:* User trials are required in order to evaluated how users interact with the sensing

system and the MAA mechanism in particular. Are users actually willing to improve the data quality in order to improve their auction bid? What are the privacy concerns of users in this context? What kind of personal information are they actually willing to reveal to the service provider? What is the real price (in Euro) that users expect in exchange for their participation in a real application scenario?

In conclusion, it is critical that users and service providers benefit from a pricing scheme, in which both parties are able to influence and express their objectives and preferences during the transaction process. Maximizing these benefits should be the next milestone down the road of applying multi-attributive auctions for allocating and pricing sensing data from users.

References

[1] N. Lane, E. Miluzzo, H. Lu, D. Peebles, T. Choudhury, and A. Campbell, *A survey of mobile phone sensing*, IEEE Communications Magazine 48 (2010), pp. 140–150.

[2] J. Burke, D. Estrin, M. Hansen, A. Parker, N. Ramanathan, S. Reddy, and M.B. Srivastava, *Participatory sensing*, in *Workshop on World-Sensor-Web (WSW '06): Mobile Device Centric Sensor Networks and Applications*, October, Boulder, CO, USA, 2006, pp. 117–134.

[3] M. Mun, S. Reddy, K. Shilton, N. Yau, J. Burke, D. Estrin, M. Hansen, E. Howard, R. West, and P. Boda, *PEIR, the personal environmental impact report, as a platform for participatory sensing systems research*, in *Proceedings of the 7th international conference on Mobile systems, applications, and services (MobiSys '09)*, 2009, pp. 55–68.

[4] S. Reddy, A. Parker, J. Hyman, J. Burke, D. Estrin, and M. Hansen, *Image browsing, processing, and clustering for participatory sensing: lessons from a DietSense prototype*, in *Proceedings of the 4th workshop on Embedded networked sensors (EmNets '07)*, Cork, Ireland, 2007, pp. 13–17.

[5] R.K. Rana, C.T. Chou, S.S. Kanhere, N. Bulusu, and W. Hu, *Ear-phone: an end-to-end participatory urban noise mapping system*, in *Proceedings of the 9th ACM/IEEE International Conference on Information Processing in Sensor Networks (IPSN '10)*, Stockholm, Sweden, 2010, pp. 105–116.

[6] N. Maisonneuve, M. Stevens, and B. Ochab, *Participatory noise pollution monitoring using mobile phones*, Information Policy 15 (2010), pp. 51–71.

[7] E. Kanjo, *NoiseSPY: A real-time mobile phone platform for urban noise monitoring and mapping*, Mobile Networks and Applications 15 (2010), pp. 562–574.

[8] R. Honicky, E.A. Brewer, E. Paulos, and R. White, *N-smarts: networked suite of mobile atmospheric real-time sensors*, in *Proceedings of the second ACM SIGCOMM workshop on Networked systems for developing regions (NSDR '08)*, 2008, pp. 25–30.

[9] P. Mohan, V.N. Padmanabhan, and R. Ramjee, *Nericell: rich monitoring of road and traffic conditions using mobile smartphones*, in *Proceedings of the 6th ACM conference on Embedded network sensor systems (SenSys '08)*, 2008, pp. 323–336.

[10] M. Paxton, *Participate: Producing A Mass Scale Environmental Campaign for Pervasive Technology*, in *6th International conference on Pervasive Computing (Pervasive 2008), Workshop on Pervasive Persuasive Technology and Environmental Sustainability*, 2008.

[11] I. Krontiris, F.C. Freiling, and T. Dimitriou, *Location privacy in urban sensing networks: Research challenges and directions*, IEEE Wireless Communications 17 (2010), pp. 30–35.

[12] I. Krontiris and F.C. Freiling, *Urban Sensing through Social Networks: The Tension between Participation and Privacy*, in *Proceedings of the International Tyrrhenian Workshop on Digital Communications (ITWDC)*, September, Island of Ponza, Italy, 2010.

[13] M. Kaenelvon , P. Sommer, and R. Wattenhofer, *Ikarus: Large-Scale Participatory Sensing at High Altitudes*, in *Proceedings of the 12th Workshop on Mobile Computing Systems and Applications (HotMobile)*, March, Phoenix, Arizona, 2011.

[14] K. Han, E.A. Graham, D. Vassallo, and D. Estrin, *Enhancing Motivation in Mobile Participatory Sensing Project through Gaming*, in *Proceeding of the Workshop in Social Connection in the Urban Spaces (SocialUrb 2011)*, October, Boston, USA, 2011.

[15] S. Reddy, D. Estrin, M. Hansen, and M. Srivastava, *Examining Micro-Payments for Participatory Sensing Data Collections*, in *Proceedings of the 12th ACM International Conference on Ubiquitous Computing (Ubicomp)*, September, Copenhagen, Denmark, 2010.

[16] J.S. Lee and B. Hoh, *Sell your experiences: a market mechanism based incentive for participatory sensing*, in *Proceedings of the 8th IEEE International Conference on Pervasive Computing and Communications (PerCom)*, March, Mannheim, Germany, 2010, pp. 60–68.

[17] S. Reddy, D. Estrin, and M. Srivastava, *Recruitment Framework for Participatory Sensing Data Collections*, in *Proceedings of the 8th International Conference on Pervasive Computing*, May, Helsinki, Finland, 2010, pp. 138–155.

[18] T. Buchholz, A. Küpper, and M. Schiffers, *Quality of Context: What It Is And Why We Need It*, in *Proceedings of the 10th International Workshop of the HP OpenView University Association (HPOVUA 2003)*, Geneva, Switzerland, 2003.

[19] K.L. Huang, S.S. Kanhere, and W. Hu, *Are you contributing trustworthy data?: the case for a reputation system in participatory sensing*, in *Proceedings of the 13th ACM international conference on Modeling, analysis, and simulation of wireless and mobile systems (MSWIM '10)*, Bodrum, Turkey, 2010, pp. 14–22.

[20] S. Spiekermann and L. Cranor, *Engineering privacy*, IEEE Transactions on Software Engineering 35 (2009).

[21] H. Xu and S. Gupta, *The effects of privacy concerns and personal innovativeness on potential and experienced customers' adoption of location-based services*, Electronic Markets 19 (2009), pp. 137–149.

[22] S. Love, *Understanding mobile human-computer interaction*, Elsevier, 2005.

[23] S. Fischer-Hübner, C. Hoofnagle, I. Krontiris, K. Rannenberg, and M. Waidner, *Online Privacy: Towards Informational Self-Determination on the Internet (Dagstuhl Perspectives Workshop 11061)*, Dagstuhl Manifestos 1 (2011), pp. 1–20.

[24] B. Skiera, M. Spann, and U. Walz, *Erlösquellen und preismodelle für den business-to-consumer-bereich im internet*, Wirtschaftsinformatik 47 (2005), pp. 285–293.

[25] P. Klemperer, *Auctions: Theory and Practice*, Princeton University Press, 2004.

[26] M. Bernhardt, M. Spann, and B. Skiera, *Reverse pricing*, Die Betriebswirtschaft (DBW) 65 (2005), pp. 104–107.

[27] E. Arevalo and M. Spann, *Consumer Acceptance of a Reverse Pricing Mech-*

anism: Content Analysis of Online Consumer Reviews, in *Proceedings of the 34th EMAC Conference*, Milan, Italy, 2005.

[28] M. Bichler, *The Future of e-Markets: Multi-Dimensional Market Mechanisms*, Cambridge University Press, New York, NY, USA, 2001.

[29] S. Strecker, *Multi-attributive auctions in electronic procurement*, Ph.D. thesis, University of Karlsruhe, Germany, 2004.

[30] M. Bichler, *An experimental analysis of multi-attribute auctions*, Decision Support Systems 29 (2000), pp. 249–268.

[31] A. Kapadia, N. Triandopoulos, C. Cornelius, D. Peebles, and D. Kotz, *AnonySense: Opportunistic and Privacy-Preserving Context Collection*, in *Proceedings of the 6th International Conference on Pervasive Computing*, May, 2008.

[32] N.F. Awad and M.S. Krishnan, *The personalization privacy paradox: An empirical evaluation of information transparency and the willingeness to be profiled online for personalization*, MIS Quarterly 30 (2006), pp. 13–28.

[33] N. Lane, S. Eisenman, M. Musolesi, E. Miluzzo, and A. Campbell, *Urban sensing systems: opportunistic or participatory?*, in *Proceedings of the 9th workshop on Mobile computing systems and applications (HotMobile '08)*, Napa Valley, California, 2008, pp. 11–16.

[34] T. Das, P. Mohan, V.N. Padmanabhan, R. Ramjee, and A. Sharma, *PRISM: platform for remote sensing using smartphones*, in *Proceedings of the 8th international conference on Mobile systems, applications, and services (MobiSys '10)*, San Francisco, California, USA, 2010, pp. 63–76.

[35] M. Shin, C. Cornelius, D. Peebles, A. Kapadia, D. Kotz, and N. Triandopoulos, *AnonySense: A system for anonymous opportunistic sensing*, Journal of Pervasive and Mobile Computing (2010).

[36] G. Danezis, S. Lewis, and R. Anderson, *How Much is Location Privacy Worth?*, in *Online Proceedings of the Workshop on the Economics of Information Security Series (WEIS '05)*, 2005.

[37] D. Cvrcek, M. Kumpost, V. Matyas, and G. Danezis, *A study on the value of location privacy*, in *Proceedings of the 5th ACM workshop on Privacy in electronic society (WPES '06)*, Alexandria, Virginia, USA, 2006, pp. 109–118.

[38] A. Acquisti, L. John, and G. Loewenstein, *What is privacy worth?*, Tech. rep., Heinz College, Carnegie Mellon University, 2009.

[39] A.B. Brush, J. Krumm, and J. Scott, *Exploring end user preferences for location obfuscation, location-based services, and the value of location*, in *Proceedings of the 12th ACM international conference on Ubiquitous computing (Ubicomp '10)*, 2010, pp. 95–104.

[40] J. Waldo, H. Lin, and L. Millett (eds.), *Engaging Privacy and Information Technology in a Digital Age*, National Academies Press, 2007.

[41] G. Iachello and J. Hong, *End-user privacy in human-computer interaction*, Foundations and Trends in Human-Computer Interaction 1 (2007), pp. 1–137.