

# Coupons as Monetary Incentives in Participatory Sensing

Andreas Albers<sup>1</sup>, Ioannis Krontiris<sup>1</sup>, Noboru Sonehara<sup>2</sup>, and Isao Echizen<sup>2</sup>

<sup>1</sup> Goethe University Frankfurt, Chair of Mobile Business & Multilateral Security  
Gruenenburgplatz 1, 60323 Frankfurt, Germany

<sup>2</sup> National Institute of Informatics  
2-1-2 Hitotsubashi, Chiyoda-ku, Tokyo 101-8430, Japan  
{andreas.albers, ioannis.krontiris}@m-chair.net,  
{sonehara, iechizen}@nii.ac.jp

**Abstract.** Participation of people is the most important factor in providing high quality of service in mobile sensing applications. In this paper we study coupons as incentives in order to stimulate users participation, especially in applications that rely on real-time data. We argue that coupons do not only function as incentives to increase user participation, but they can also direct more people to the targeted sensing area, increasing the overall utility of data for service providers. In this paper we study coupons in combination with multi-attributive auctions, which gives the additional advantage to service providers of not having to determine the coupon value that users would expect in exchange for their data. Instead users have to compete with each other to win the auction, choosing coupons of lower values. Even though the combination of coupons with multi-attributive auctions is very attractive for participatory sensing, we also highlight some of the problems coupons have and especially those connected with user 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-localised 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, enabling new large-scale practices.

An interesting class of applications that emerged from these advancements shares the vision of a sensor data-sharing infrastructure, where people and their mobile devices provide their collected data streams in accessible ways to third parties interested in integrating and remixing the data for a specific purpose or 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 [3, 4]. 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 [5] or road and traffic conditions [6].

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, it remains questionable how the general public can be motivated to participate, especially since efforts that call people to freely volunteer have only been moderately successful so far.

From the viewpoint of service providers that collect 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. Monetary incentives can be of the form of micro-payments, but they can become even more attractive in the form of coupons, which are nowadays easily transferable in electronic form on consumers’ mobile phones and offer additional advantages from the perspective of service providers.

The challenge then becomes how to determine the price that users expect to receive for their effort of collecting 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 [7]. In general, each user has her own valuation and thereby a minimum price that he expects to receive, depending on how much effort and personal information he has to give out, 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.

In this paper we argue that an attractive solution to the above problems is the use of multi-attributive auctions, because service providers avoid determining the price, but they rather delegate it to the users, who are bidding and competing with each other, pushing the prices down. In our solution however, we use coupons instead of micro-payments, which offer additional advantages. One of the main advantages is that coupons can incentivise people to move towards the targeted area, where we want to collect data from, and at the end increase the flow of data to the service provider. However, coupons also introduce additional difficulties and have an impact on how the auction mechanism should be organised. In particular, in this paper we study how coupons can be integrated into multi-attributive auctions and how the utility of the data at the service provider is affected.

The rest of the paper is structured as follows. In Section 2, we argue why multi-attributive auctions are the appropriate pricing mechanism for participatory sensing, we argue about the impact of using coupons instead of micro-payments and we describe analytically the steps of the auction mechanism with coupons. In Section 3, we discuss the parameters that affect the valuation of coupons by users and what additional context parameters can affect the overall

utility of the submitted data by the service provider. Section 4 presents our experiments results and Section 5 highlights the privacy concerns associated with coupons. Finally, in Section 6 concludes the paper.

## 2 Market-based Acquisition of Sensing Data

Reddy et al. [2] demonstrated with user trials that a set of micro-payments can be effective in encouraging participation in mobile sensing. 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 for a balanced participation. In this regard, micro-payments constitute very strong means to influence users in favour of a service provider.

However, service providers offering fixed prices for the acquisition of sensing data cannot address the diversity of the resource “sensing data”. As discussed above, the price that users expect to receive for their efforts is different among individuals and depends on many parameters. So, a better alternative for a pricing scheme would be to use auctions that could help to reveal the expected, unknown price of a user for her contribution.

Lee and Hoh [8] 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. Reverse auctions lead to the decrease of prices, since sellers (mobile users) compete with each other and continuously decrease their bids to increase their chances to win [9]. The winners of the auction round are able to sell the sensing data to the service provider at the price of their bid.

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 her 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[10]. 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 data and therefore does not help service providers meet their application and quality of service requirements.

In [11], we showed that multi-attributive auctions (MAAs) are an attractive solution in the paradigm of participatory sensing, since they can help service providers select the most suitable sensing data, but also provide users with the incentive to improve on them. This mechanism provides attractive benefits for participatory sensing and in particular:

- (i) Service providers can avoid the challenge of determining the price a user expects to receive for her 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, but they have 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.

## 2.1 Replacing micro-payments with coupons

Monetary incentives used to motivate users in order to participate in activities for a service provider typically consist of money in the form of micro-payments. Another form of payments in this context is coupons, which are handed out as part of loyalty programs. This kind of coupons allows users to get discounts on selected products at participating retail stores (e.g. buy two - pay one). In recent years, such coupons have become more and more digital, which makes them easy to transfer electronically to a mobile wallet or to a loyalty eCard of a user (i.e. similar to digital money transfers). Nevertheless, coupons differ from real money in certain aspects, which in our context can provide additional benefits to service providers wanting to reward users in exchange for sensing data.

Although, there is great variety of different types of coupons available in practice, they all share three common characteristics: coupons can only be redeemed for specific products (e.g. lunch meal), at a specific retailer (e.g. Italian restaurant) and in a specified context (e.g. only in restaurants in a certain city within the next two month). Service providers can leverage these characteristics to their advantage in order to increase the utility of their collected sensing data, if they are also willing to address the complementary drawbacks.

One of the advantages is the possibility to make coupons location-dependent and motivate users to collect required data from a specific geographic region, by handing out coupons, which are only valid in a certain part of a city (around this area) and have at the same time a short expiration date. This can motivate users who are already in the area to sense data or most importantly make users move to that targeted area from other points. Existing research has already demonstrated empirical evidence for this through user experiments on the factors leading individuals to redeem coupons [12]. The findings suggest that the main drivers for this are the distance to the shop, the amount of discount, the time of day and the matching of coupon with user profile.

An addition benefit of using coupons is that service providers act as distributors/promoters of coupons and may receive a monetary compensation from retailers in exchange. This allows them to lower the total sensing data acquisition costs.

One should note here that even though the fact that a coupon can only be redeemed for a certain purpose is beneficial for retailers, it is at the same time a

drawback for the user. While money can be spent virtually everywhere, a coupon can only be used for certain purpose (product, brand, etc.), which a user may or may not value at all. Thus, coupons are always less worth to users than money.

Besides this obvious challenge for service providers to leverage the advantages of coupons while taking care of the drawbacks, coupon characteristics also make it more challenging to integrate them in multi-attributive auction mechanisms. As we said above, we employ MAAs, in order to determine the price that a user demands for her sensed data. If real money is used in the auction, the user can simply specify the price at which he is willing to sell. Coupons, on the other hand, have two monetary values. The first value (internal value) is determined by the objective amount of money a user can save by redeeming the coupon. The second value (external value) is determined by the personal valuation of the user for such a coupon. That is, the value of a coupon depends on the value a user sees in a product, for which the coupon offers a discount. Consequently, the challenge for service providers is to consider both values of a coupon in the multi-attributive auction mechanism.

In the next section we suggest a solution of how coupons can be integrated in multi-attributive auctions and we show analytically the steps of one auction round applied in the context of participatory sensing applications

## 2.2 Auction Process

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.

Fig. 1 depicts the three more generic phases of the process, but in what follows we explain in details the specific steps involved.

*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 a *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. Basically, it allows the service provider (buyer) to communicate its quality requirements for a good, so that the mobile user (seller) is able to address these requirements alongside the submission of her monetary bid.

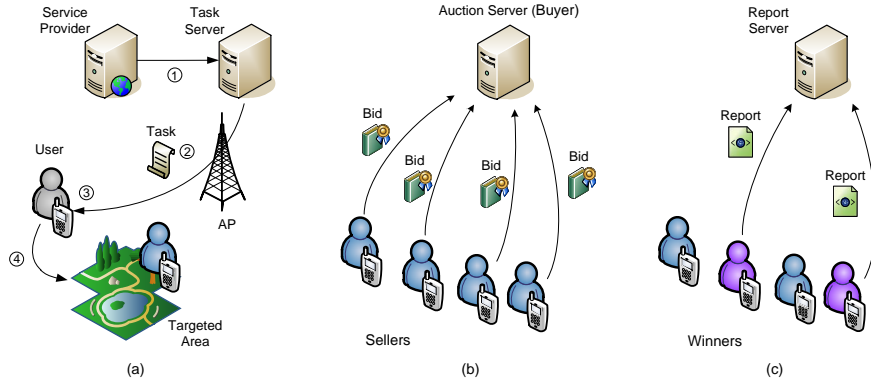


Fig. 1: The three phases of applying multi-attributive auctions for the acquisition of sensing data.

*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. As we discussed in Section 2.1, since service providers are giving out coupons instead of real money, specifying an actual price as in regular auctions does not work anymore. Instead, the user is presented with a set of coupons to choose from. Thereby it is essential for a service provider to select carefully, which coupons should be in such a predefined set. The challenge is to match the interests of the service provider and the user. The interest of the service provider is to motivate users to sense data in a certain geographic region and (if applicable) at the certain time. The user on the other hand is interested in receiving coupons that are close to her current location and match her personal product preferences. Consequently, if a user accepts a sensing task, service providers need to select coupons based on a user's current location and personal preferences profile.

However, coupons are only the monetary part of the user's bid (i.e. the internal value of a coupon that the user chooses). Multi-attributive auctions integrate additional attributes of a good into the auction bid, besides the price. So, each bid comprises a monetary bid as well as a multiple quality dimension. In particular, a bid is represented as  $n$ -dimensional vector  $Q$  of both monetary and non-monetary relevant attributes.

In the case of an additive utility function  $S(x_j)$ , the bid of the user (seller) can be expressed as  $x = (x_1, \dots, x_n)$ . The service provider (buyer) evaluates each relevant attribute  $x_j$  through the utility function. As a result, the function  $S : Q \rightarrow IR$  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  $w_1, \dots, w_n$  summing up to the value of one. The overall utility of bid is given by Equation 1.

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

So, in this step the utility function  $S(x)$  is evaluated, in order to produce the utility score. This operation is locally at the device and does not involve any communication. The mobile device already has all the information needed to compute  $S(x)$ . In Section 3, we discuss several concrete parameters that could function as attributes of the utility function.

*Step 4:* If not satisfied by the utility score, users can improve it, by acting on the data quality factors (i.e. on the attributes  $x_i$ ). For example, a user could choose a coupon with smaller value, or blur the location information (for location privacy protection), or move closer to the preferred sensing area of the service provider (as shown in Fig. 1(a)) and provide more accurate data.

*Step 5:* The utility score is recalculated locally at the user's device and once the user is satisfied with the value, he submits her bid to the Auction Server for the current auction round, as shown in Fig. 1(b). Her bid is not the data itself, but rather the utility score, i.e., the characteristics of the sensing data. The auction round begins at the end of each reporting time period and takes place between the users who have submitted their bids in that round.

For  $m$  submitted bids, the buyer determines the winning bid to be the one with the maximum utility score, as given by Equation 2.

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

However, in most applications it would not be enough to have only one winner and therefore only one data report. In that case, Equation 2 can be generalised to select the bids with the  $n$  biggest utility scores and that consequently determines  $n$  winners for the auction round.

*Step 6:* After the auction round winners have been determined, they get notified by the service provider and they submit the actual sensing data from their devices to the Report Server. This is depicted in Figure 1(c). The rest of the users who lost this auction round do not submit their data, but their probability to win in the next round is increased, as we will see in the next section.

*Step 7:* Finally, the service provider transfers the coupons to the winning users. If the users actually redeem the coupon in the specified retail store, their action is fed back to the service provider as well as the retailer. For the service provider, this information is valuable in terms of refining the preference profile of the user in order to suggest relevant coupons for a user to choose from in the next auction round. In that way we keep the external coupon value at a high level, which would be necessary for the coupons to keep working as incentives. At the same time, for retailer this information provides a variety of insights as

well (e.g. at which location and time has a user received the coupon, did he actually redeemed the coupon, etc.)

### 3 Assigning Attributes to Sensing Data

As we saw in the previous section, the service provider (buyer) defines a utility function  $S(x)$  beforehand, including multiple attributes  $x_i$  that is important to him and on which users will compete during the auction. Each attribute is weighted differently, by assigning the corresponding weight  $w_i$ . Then, the question becomes: what are those attributes that the service provider can include in the utility function? The obvious one is the selling price requested by the users, which the service provider wants to keep low and within the available budget. Below we discuss a list of additional attributes. We use the Quality of Context framework of Buchholz et al. [13] 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.

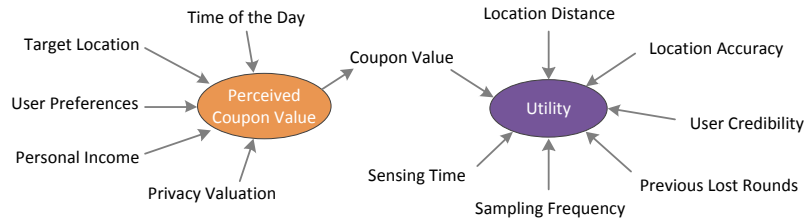


Fig. 2: Parameters affecting the utility function,  $S(x)$ .

*Coupon Value:* The coupon value needs to be described from two perspectives. First, there is an internal value for each coupon. It denotes the actual costs of a retailer in the case a user actually redeems a coupon (e.g. 30 percent off). Second, there is an external value of a coupon, which reflects its personal valuation by a user. This valuation is determined by several factors:

- (i) **Time of the Day:** Coupons need to be redeemable in short period of time for users. If this is not possible (e.g. due to certain opening hours of a retailer), this may decrease the value of a coupon for a user.
- (ii) **Target Location:** The same as above applies to location. If the distance between the issuing retail shop and the user is too large, it takes correspondingly long time for the user to redeem this coupon. Consequently, it decreases the value of a coupon for that user.
- (iii) **Personal Income:** A coupon allows a user to save a certain amount of money. The perceived value of this is determined by the personal income of that user: The higher the income, the lower the external value of the coupon.



- (iv) **User Preferences:** Each user has personal preferences about certain products and he values them differently. Consequently, the external value of the coupon for a user is determined by how close the coupon manages to address her personal preferences.
- (v) **Privacy Valuation:** In order to offer users relevant coupons, service providers have to know the current location and personal preferences of a user, which directly affects her privacy. Then, the perceived value of the coupon for that user will be affected by this trade-off and her overall privacy attitude.

Eventually, the external value determines the internal value of a coupon, since the users are given the opportunity to choose amongst a set of coupons. A user will always choose a coupon based on its external value (i.e. the personal value of a coupon for him), which determines the internal value and therefore the costs for a retailer/service provider. Nevertheless, during the auction the user is able to decrease her bid, in order to improve her winning position. That corresponds to choosing a coupon with smaller value out of the available coupons and resubmitting her bid, as described in Section 2.2.

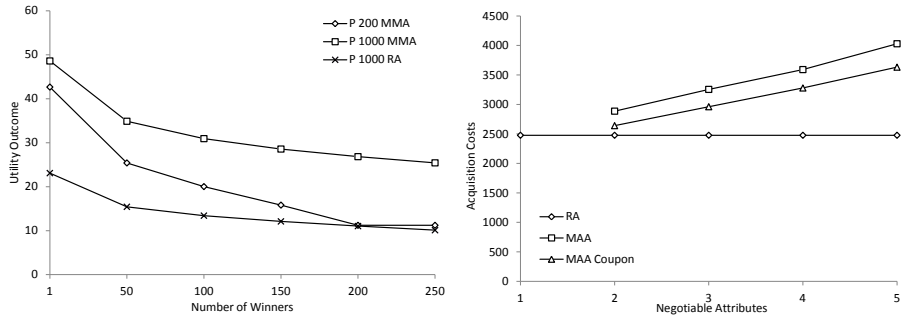
*Amount of submitted data:* The sampling frequency and the overall time the sensors are measuring the environment affect the energy resources of the user's mobile phone. By increasing them, the user would devote more resources, but also increase the data quality and therefore the utility score.

*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 [14]. 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 bidding 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 her 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.



(a) Utility dependence on the number of winning users. (b) Acquisition costs as a function of the negotiable attributes with users.

Fig. 3: Simulation results

## 4 Simulation Experiments

In our experiments, we compare the traditional Reverse Auction (RA) format with the multi-attributive auction format. The resource *sensing data* is described by the coupon value and a number of quality attributes, as described by Eq. 1. For the sake of simplification we have assumed equal weights for all attributes, unless stated otherwise. 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 [9]. Based on the *Monte Carlo Simulation* model, 5000 auction rounds had been conducted for each simulation case below.

In the usual case in participatory sensing, we will require the data of several sources, in order to cover a geographical area efficiently. Fig. 3a shows how the utility for service providers changes, if more than one users can win the auction. In particular, the figure shows two cases for MAA (for 200 and 1000 overall participants). The figure also demonstrates how the utility score in MAAs compares with the simpler case of Reverse Auction, where users negotiate only on one attribute (the price). In both cases the utility outcome drops as the number of winners increases. 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. 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 emphasise that the MAA case still provides a higher overall utility than the RA.

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. For simplicity, only one winner of the auction was assumed. The results are shown in Fig. 3b and they demonstrate that the acquisition costs for

service providers increase, once we apply MAAs and the coupon value is no longer the only attribute to be negotiated. This is because users are no longer solely competing on the coupons and instead competition is now equally distributed across multiple attributes on sensing data. However, a service provider has the option to increase the weight for the attribute “coupon value” within the utility function. This case is denoted as “MAA Coupon” in Fig. 3b. Thereby, the service provider is able to reach a trade-off between acquisition costs and utility outcome based on the requirements of the application and business model. This means, the higher the weight on the coupon value, the lower the acquisition costs and also the lower the overall utility outcome.

## 5 Discussion

The main advantage of replacing micro-payments with coupons for sensing data is to increase the attraction of users towards a desired sensing target area. Indeed, user surveys have shown that up to 68% of people find location-based coupons attractive [15]. At the end this would increase the utility of sensed data for service providers. In addition, coupons will generate additional revenues coming from coupon-issuing retailers, as we mentioned in Section 2.1.

However, these benefits come at the expense of user privacy. First of all, service providers have to be aware of the product preferences or immediate needs of a user, in order to be able to offer attractive coupons in exchange for sensing data. This kind of information typically has to be provided by retailers and enables access for the service provider to all user preference information from related retailers to which a user has subscribed.

In addition, once users redeem a coupon while buying a product, they disclose their product preferences as well as their current location (i.e. location of the retailer). This privacy problem does not only link to the retailers but also to the sensing platform provider. This is because the retailer will eventually forward this information back to the service provider, in order to improve its future ability to offer attractive coupons to users (closed-looped marketing).

In order to develop a viable business model for the service provider, the outlined privacy issues need to be addressed by further research that allows to balance between stakeholder benefits (i.e. service providers, retailers, and users) and privacy protection. As there is currently no good solution for this, it is also important to equip users with the ability (e.g. transparency and control) to make informed decisions on the trade-off between monetary incentives and privacy.

## 6 Conclusions

The combination of coupons with multi-attributive auctions can create a powerful solution for service providers that want to offer monetary incentives to mobile users in the context of participatory sensing applications. It enables service providers to negotiate with users for a higher quality of sensing data. Especially the use of location-based coupons can incentivise more people to move in the

targeted sensing data increasing the utility of data even further. Furthermore, service providers have additional economic benefits, since users compete with each other and drop the prices they ask for their data. Coupons bring additional revenue coming from the retailers issuing the coupons. However, coupons introduce also important privacy threats for the users that need to be addressed. User trials are required here, in order to evaluate how users would behave in practice in their interaction with the MAA mechanism and how this behaviour is affected by their privacy concerns. Our future research is targeted in this direction.

## References

1. Lane, N., Miluzzo, E., Lu, H., Peebles, D., Choudhury, T., Campbell, A.: A survey of mobile phone sensing. *IEEE Communications Magazine* **48**(9) (2010) 140–150
2. Reddy, S., Estrin, D., Hansen, M., Srivastava, M.: Examining micro-payments for participatory sensing data collections. In: *Proceedings of the 12th ACM International Conference on Ubiquitous Computing (UbiComp)*. (2010)
3. Maisonneuve, N., Stevens, M., Ochab, B.: Participatory noise pollution monitoring using mobile phones. *Information Policy* **15** (2010) 51–71
4. Kanjo, E.: NoiseSPY: A real-time mobile phone platform for urban noise monitoring and mapping. *Mobile Networks and Applications* **15** (August 2010) 562–574
5. Honicky, R., Brewer, E.A., Paulos, E., White, R.: 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)
6. Mohan, P., Padmanabhan, V.N., Ramjee, R.: 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) 323–336
7. Krontiris, I., Freiling, F.C., Dimitriou, T.: Location privacy in urban sensing networks: Research challenges and directions. *IEEE Wireless Communications* **17**(5) (October 2010) 30–35
8. Lee, J.S., Hoh, B.: 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)*. (2010)
9. Bichler, M.: *The Future of e-Markets: Multi-Dimensional Market Mechanisms*. Cambridge University Press, New York, NY, USA (2001)
10. Boutsis, I., Kalogeraki, V.: Dynamic QoS-aware event sampling for community-based participatory sensing systems. In: *Proceedings of the 6th ACM International Conference on Distributed Event-Based Systems (DEBS '12)*. (2012) 153–156
11. Krontiris, I., Albers, A.: Monetary incentives in participatory sensing using multi-attributive auctions. *International Journal of Parallel, Emergent and Distributed Systems* **27**(4) (2012)
12. Spiekermann, S., Klafft, M.: Elektronisches couponing: Wetter schön hohe coupon-einlöseraten. *Absatzwirtschaft* **8**(2) (2006) 4–9
13. Buchholz, T., Küpper, A., Schiffers, M.: 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)
14. Kapadia, A., Triandopoulos, N., Cornelius, C., Peebles, D., Kotz, D.: AnonySense: Opportunistic and privacy-preserving context collection. In: *Proceedings of the 6th International Conference on Pervasive Computing*. (May 2008)
15. Acardo: Akzeptanz von mobile couponing. Technical report, Acardo / lb-lab (2011)