Examining Micro-Payments for Participatory Sensing Data Collections

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Examining Micro-Payments for Participatory Sensing Data Collections

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ABSTRACT
The rapid adoption of mobile devices that are able to capture and transmit a wide variety of sensing modalities (media and location) has enabled a new data collection paradigm - participatory sensing. Participatory sensing initiatives organize individuals to gather sensed information using mobile devices through cooperative data collection. A major factor in the success of these data collection projects is sustained, high quality participation. However, since data capture requires a time and energy commitment from individuals, incentives are often introduced to motivate participants. In this work, we investigate the use of micro-payments as an incentive model. We define a set of metrics that can be used to evaluate the effectiveness of incentives and report on findings from a pilot study using various micro-payment schemes in a university campus sustainability initiative.

Author Keywords
Participatory sensing, incentives, mobile sensing systems

ACM Classification Keywords
H.5.m Information interfaces and presentation (e.g., HCI): Miscellaneous.

General Terms
Design, Experimentation, Human Factors

INTRODUCTION
Mobile phones are increasingly able to sense a variety of modalities. These familiar devices already record text, images, and location information. When users are involved in deciding what data to collect, it is referred to as participatory sensing [5, 6, 13]. Many interesting technical and user interface challenges exist in participatory sensing [2, 14]. One of these is the design of mechanisms that encourage individuals to contribute information towards the sensing task. Recent participatory sensing projects have explored different methods to motivate individuals to participate. Techniques have included highlighting the altruistic nature of data collections (gathering information for ecological efforts in EpiCollect), providing beneficial personal analytics (bicycle ride details in Biketastic), enabling data bartering to obtain additional information (bargain hunting through price queries in LiveCompare), and involving individuals in challenges (traffic monitoring with treasure quests in Waze) [1, 16, 8, 18].

In this work, we explore incentives based on micro-payments, i.e., transactions in which small tasks are matched with small payments. We consider various micro-payment models including different set amounts per sample and a dynamic payment in which competition determines the per sample payment rate. These micro-payment schemes are compared to the base case of a lump sum macro-payment for the data collection as a whole. We define a set of standard participation and performance metrics that can be used to evaluate the effectiveness of incentive models in data collections and report on findings from a pilot study. The results from the study lead to design guidelines in how to create and organize payment based incentives for participatory sensing projects.

RELATED WORK
Micro-payments have been used in a variety of e-commerce settings. Initially, they were introduced as a potential method to meter web content usage through users paying based on page visits to a site [17]. More recently, micro-payments have become a popular transaction mechanism for buying music and applications [9]. They have also played a role in controlling "free-riders" in peer-to-peer systems by charging for individuals for downloads and replenishing credit based on sharing habits [10]. Finally, micro-payments have been explored as a method to alter consumer behavior towards sustainable habits [19].

Amazon Mechanical Turk (MTurk) has used micro-payments as an incentive tool for task fulfillment [3]. Specifically, MTurk is a market-place where requesters post tasks that are easy for humans to perform but difficult for computers to complete. Workers complete tasks in exchange for a micro payment. The work of [12] has shown that in MTurk increasing the amount of payments typically causes tasks to be completed faster but does not necessarily improve quality. Although MTurk and participatory sensing are related in that small tasks are asked to be performed by individuals, participatory data collections differ significantly in that individuals contribute sensed information during their daily routines and are connected to the context and purpose of their tasks.

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Aside from micro-payments, it has been shown that lump sum macro-payments can increase participation in surveys [4, 7, 11]. This has been a common practice for health, economic, and market research surveys. We build on this related work but concentrate on using micro-payments for mobile sensing tasks and analyze the effects of different payment schemes on participation frequency, quality, and coverage.

METHODOLOGY

In this section, we describe the application context of the participatory sensing experiment as well as the system used for the study. Finally, deployment setup details along with metrics to evaluate incentive models are provided.

Application Setting

The target application for our incentive study was an effort to learn about recycling practices at a university. Participants were asked to take photos, Figure 1 a.), of the contents of outdoor waste bins (over 700 exist on campus) and optionally label the images with tags that indicated their contents (waste or recyclable type) and proximity to recycling clusters. Although these tags are useful, they were made optional since inputing them adds additional time to the sampling process, and since they can be inferred offline if needed. The university maintenance department will use the collected data from the study to improve placement of recycling bins.

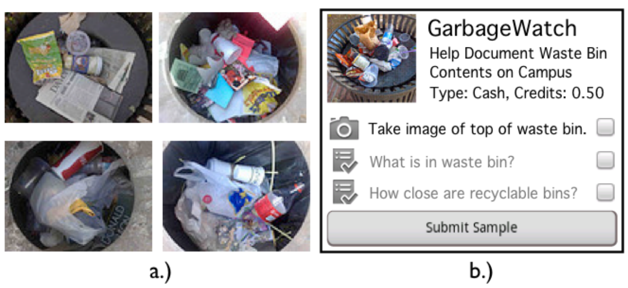

Figure 1. Data Collection Images and Mobile User Interface

System Details

To support the data collection, a mobile phone application was developed for the Android G1 that enabled participants to capture geo-tagged images and optional tags. The application uploaded collected information to a backend datastore automatically. Participants were presented with the incentive amount each time they took a sample - as shown in Figure 1 b.). In addition, individuals were able to view the overall amount of payment earned.

Deployment Details

Fifty-five individuals were recruited for the pilot study using flyers distributed throughout campus. The participants consisted of 25 males and 30 females between 18 and 28 years old. They were divided randomly into one of five incentive groups (11 per treatment): lump sum payment (MACRO), medium micro-payment (MEDIUMμ), high micro-payment (HIGHμ), low micro-payment (LOWμ), competition based micro-payment (COMPETEμ). The resulting groups were generally balanced in terms of males to females represented.

The participants were briefed on the purpose and length of the study, trained on how to collect images, and informed only about their specific incentive. Also, participants were told that only clear (not blurry or too dark) images of waste bin contents are valid and that the tags listed as optional were in fact desired. The study ran for a 5-weekday span, and participants were asked to capture waste bin contents as long as the same bin had not been sampled 30 minutes prior by them. Five days was chosen as the length based on observing when participant fatigue occurs in previously run data collections of a similar type [15]. Reminder emails were sent about data collection procedures, payment earned, and the time remaining to participate.

MACRO promised individuals 50 dollars for involvement in the study. MEDIUMμ, HIGHμ, and LOWμ involved 20, 50, and 5 cents per valid submission respectively. COMPETEμ payment was based on ranking among peers determined by the number of samples taken (which was reset daily) and ranged from 1 to 22 cents per valid submission. COMPETEμ members had access to all participant ranking / submission numbers in real-time on the phones. The total pay out for the micro-payments was capped at 50 dollars per participant.

Measurement Parameters

To understand the characteristics of different incentive plans, we consider the following participation and performance metrics: quantity, quality, and coverage.

- **Quantity** - Represents the number of samples that were taken by a participant. It can be compared over different time intervals that make up the data collection period (for instance, submissions per hour or day).
- **Quality** - Describes the ability of a processing system to determine a particular feature of interest. It can be affected by sensor characteristics, participant capturing ability, and the thoroughness of information provided.
- **Coverage** - Embodies the spatial and temporal extent associated with samples provided by participants. Different resolutions for space and time can be defined based on the individual data collection specifications.

Other factors include relevancy, likelihood, timeliness, and responsiveness [15]. These metrics were not evaluated in this study because the outdoor waste bins were distinctive, constant location tracing was not enabled due to battery concerns, automatic image uploading occurred, and no events existed that needed immediate participant attention.

PILOT STUDY FINDINGS

In this section, we analyze the results from our pilot data collection. For our experiment, quantity is defined by the number of waste bin images submitted overall along with participation over the 5-weekday span. Quality is measured by analyzing the percentage of invalid waste bin images (blurry, too dark) contributed by participants along with the percentage of optional annotations provided that detailed if recyclables or waste existed and the closeness of recycling clusters. Coverage is computed by evaluating the number of spatial blocks and temporal periods covered by the participants in the study. In addition to these qualitative measures, a post-data survey was administered that tried to learn about how much each incentive motivated participants to collect data. Also, questions existed so information about the coverage and data quality behaviors of participants can be ascertained.

Participation

The number of submissions made under each incentive treatment is shown in Table 1. Overall, the most successful incentive protocol in terms of participation was the competition based micro-payment system, and the least successful one was the flat lump sum payment model. Although COMPETEμ had the highest output, the individual user participation rates varied greatly. From analyzing the participation patterns of COMPETEμ, three groups can be distinguished. Essentially, there existed three members that were highly motivated to be in first place ("the winner") and thus contributed above normal, five individuals that were competitive but participated within their means, and three participants where the competition was in fact a turn off.

Incentive Type	Total	Median	IQR	Max	Min
MACRO	1291	69	163	285	35
MEDIUMμ	2613	262	177	368	83
HIGHμ	1533	132	30	182	103
LOWμ	2145	137	228	491	46
COMPETEμ	5256	450	664	1361	38

Table 1. Overall Data Collection Participation Output

In general, the set micro-payment models were more successful then the lump sum incentive. This occurred due to participants having to earn their payment and because of self-competition. For instance, HIGHμ individuals indicated that their initial goal was to reach a 100 images to get the 50 dollar cap in earnings, but then they continued to contribute to see how much payment they could accumulate "just for fun." Finally, several MACRO participants stated that they had a difficult time judging what 50 dollars was worth in submissions and thus simply slowed down after a few days since they believed they did enough to deserve the payment.

Furthermore, the average and individual participant submission percentage for each day of the 5-weekday span is shown in Figure 2. Both MACRO and COMPETEμ had decreases in participation towards the end of the data collection period. In the case of MACRO, participants lost the novelty of the exercise as the week went on. COMPETEμ individuals indicated that they "burned out" after the first few days and that the "i don't want to lose nerve" turned off. Set micro-payment participants stated that they either tried to take as many images as possible each day or paced their submissions out to achieve a certain total by the end of the week. But when their plan to spread out sampling failed, the participants typically "ramped up" their submissions in the last few days. Overall, providing a fair micro-payment (MEDIUMμ or HIGHμ) with an achievable max pay out seems to be a good strategy to have balanced participation throughout the week.

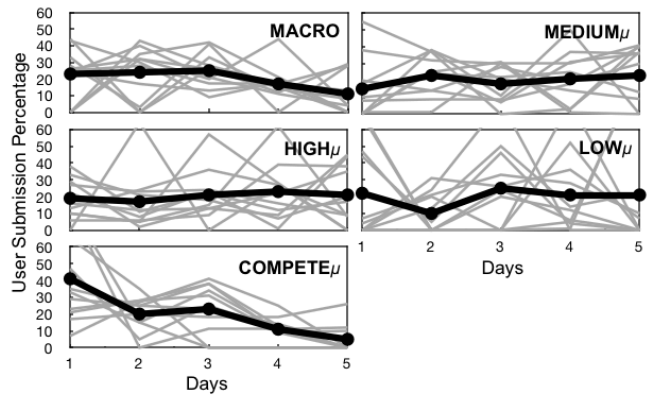

Figure 2. Daily Submission Percentage (Avg - Black, Individual - Gray)

Quality

Next, data collection quality for the incentive models is analyzed. Table 2 contains the average percentage of invalid waste bin images (blurry, too dark) provided per participant along with the average percentage of optional tags added to submissions per participant. The validity of the images were labeled manually. Overall, the percentage of invalid images for all the incentive types was relatively low. These results are consistent with expectations - participants were motivated to take good photos for different reasons. In MACRO, there was no time pressure associated with the task since participants were already promised the payment. The micro-payment schemes motivated individuals to take valid photos since only clear ones would result in payment and taking invalid photos would be a waste of time. Also, participants commented that re-capturing photos was quick enough that they often did that when blurry ones were initially taken.

In COMPETEμ, participants submitted significantly fewer optional tags than the other incentive types. Individuals indicated that they "started skipping that step to get more trash cans" because they felt "pressure" to keep up with competitors. Participants in the other incentive groups generally were more inclined to add the tags since they "felt that it would help further the study" and that adding the annotations did not seem like "that much more work."

Incentive Type	Avg % of Invalid Pics per User	Avg % of Optional Tags per User
MACRO	7$\pm$5	70$\pm$21
MEDIUMμ	6$\pm$4	47$\pm$25
HIGHμ	6$\pm$3	60$\pm$25
LOWμ	5$\pm$3	52$\pm$24
COMPETEμ	6$\pm$3	6$\pm$4

Table 2. Quality of Participation (Participant Avg % $\pm$ .95 CI)

Coverage

To analyze the coverage provided by participants, we discretized space into 10000 m^2 blocks (114 in total) empirically to account for GPS inaccuracies and waste bin spread and divided time into 30 minute periods to account for the daytime hours of the 5-weekday span (120 in total). The coverage results are shown in Table 3. COMPETEμ resulted in the highest average spatial and temporal coverage provided by participants followed up by the set micro-payment models and then the lump sum payment. Overall, participants in COMPETEμ sought out as many sampling opportunities as possible and often explored "parts of the school that [they] never been to" and even spent extra time on campus. The set micro-payment individuals did not necessarily change their routines but would instead "walk to trash cans that were visible but not in [their] path." MACRO individuals focused on waste bins that were along their normal path.

Incentive Type	Avg # of Locations Blocks per User	Avg # of Time Periods per User
MACRO	16±6	16±6
MEDIUMμ	24±5	19±3
HIGHμ	17±4	18±3
LOWμ	22±5	19±4
COMPETEμ	31±10	27±9

Table 3. Location and Temporal Diversity (Participant Avg # ± .95 CI)

DISCUSSION

We observed consistent patterns during this initial small-scale study of payment based incentives. First, monetary incentives were more beneficial when combined with other motivating factors such as altruism or competitiveness (self or with others) - often increasing interest in participating and reinforcing good data collection habits. In general, the set micro-payments were the most effective in encouraging participation throughout a data collection since they enabled participants to setup daily "goals" in terms of amount of money to earn. Micro-payments based on competition might be better suited for short bursty data collections unless mechanisms are added to offset participant fatigue. Making the incentive payment fair for all participants was important - very low baseline micro-payments discouraged individuals even when the potential to earn money existed. Also, if properly designed, micro-payments have the potential to extend participant coverage both spatially and temporally. In general, the specific parameters associated with micro-payments are likely to differ from one data collection to another, so short trials might be beneficial to test the sensitivities of the target population within the target context.

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