CampusTracker: Assessing Mobile Workers' Momentary Willingness to Work on Paid Crowdsourcing Tasks

Jonas Oppenlaender
University of Oulu
90014 Oulu, Finland
jonas.oppenlaender@oulu.fi

Simo Hosio
University of Oulu
90014 Oulu, Finland
simo.hosio@oulu.fi

Kennedy Opoku Asare
University of Oulu
90014 Oulu, Finland
kennedy.opokuasare@oulu.fi

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Abstract

In mobile crowdsourcing, labour can be opportunistically elicited by sending notifications to workers who complete tasks on-the-go. While much work has focused on optimizing the work quality and quantity in mobile crowdsourcing, surprisingly few studies have explored the type of tasks that might be suitable for different user contexts. This paper presents results from a proof-of-concept user study that aimed to uncover where, when and what type of tasks mobile workers are willing to complete. We find that different contexts do affect the type of work users are willing to complete. Finally, we lay out a complete design, key challenges and opportunities for a longer field trial that we hope to conduct in the near-future.

Author Keywords

Mobile Crowdsourcing; Experience Sampling Method; Ecological Momentary Assessment.

ACM Classification Keywords

• Information systems → Crowdsourcing; • Human-centered computing → Mobile computing; User studies;

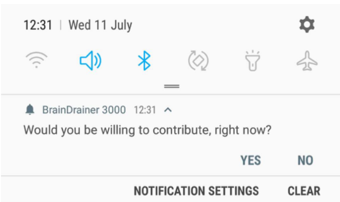

Figure 1: Screenshot of notification with action buttons.

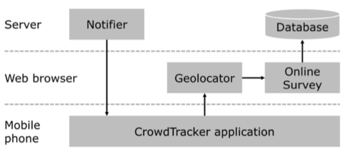

Figure 2: CampusTracker architecture and data flows.

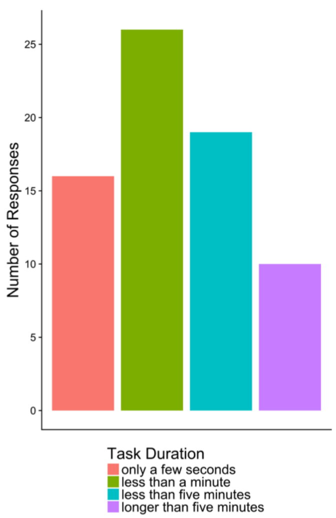

Figure 3: Task duration (n=71).

Introduction

Paid crowdsourcing refers to distributing work as small tasks to the crowd for a monetary reward via an open call for participation [1]. Mobile crowdsourcing can be used to complement online crowdsourcing in various ways, for example in better exploiting local knowledge [2]. Yet in paid mobile crowdsourcing, a worker is not always self-selecting to "work now" on a given type of task, as is typically the case in online crowdsourcing. Instead, registered workers can be opportunistically invited to contribute using *e.g.* mobile push notifications.

In the fields of Ubiquitous Computing, HCI and crowdsourcing, context has been shown to affect user behaviour. Typically, context is defined as explicit and implicit situational information [3]. While the user's willingness to donate data has been studied extensively in mobile crowdsourcing [4], surprisingly little work exploits the opportunity of opportunistically distributing tasks in contexts that best suit the tasks: situations and moments that support and accommodate a specific type of work.

In this paper, we set to study how the mobile worker's context affects the willingness to complete different types of paid tasks. Our prototype, called *CampusTracker*, sends notifications to the users' mobile devices at random times during the day, inquiring about the users' willingness to complete different types of tasks in the users' current prevailing context. We explore this question by deriving qualitative insights from data and interviews acquired in a small-scale but realistic field study. Using the derived insights, we discuss our plans for creating an on-campus mobile crowdsourcing system that supports distributing tasks to users in their optimal contexts.

Related Work

For studying the context of mobile users, the Experience Sampling Method (ESM) [5] has been applied as a reliable approach. Particularly with the advent of powerful smartphones, the ESM allows to collect data from mobile users about both the user's context as well as the user's personal state and opinions [6]. Micro Ecological Momentary Assessment (µEMA) [7] has further proven to be a method suitable for encouraging users to contribute data from their mobile phones.

Numerous studies in the area of context-aware mobile crowdsourcing either assume a homogenous user profile, *e.g.* [8], or consider the location as primary factor determining the context of the mobile worker, *e.g.* [9]. [10] describe a context-aware system that automatically recommends bundles of tasks to mobile workers based on predictive probabilistic models assembled from contextual variables, such as the history of the user behaviour, skills, and location.

CampusTracker

To study how context affects people's willingness to complete different types of paid tasks on mobile devices, we implemented *CampusTracker*, a simple mobile application that acts as a notification gateway. The application alerts its users by sending push notifications (seen in Figure 1).

The application was built using Monaca (monaca.io), a cross-platform application builder, and Google Firebase for the notification infrastructure. The application supports both Android and iOS. We scheduled the push

Task type	#
Poll, e.g. voting	71
Data, e.g. tagging, categorization, cleansing	39
Moderation of comments, images, videos	39
Transcription of audio, video, images	12
Copywriting	7

Table 1: Task types (n=71).

Input method	#
Radio buttons	71
Checkboxes	66
Dropdowns	60
Writing (short text)	23
File uploads/camera	13
Writing (long text)	5

Table 2: Input methods (n=71).

notifications with a Python script. We also deployed a thin online gateway between the surveys and the application, to detect the user's location via the Geolocation API of the phone's Web browser. Figure 2 depicts the overall architectural design of CampusTracker.

Study Design

After a brief internal 3-day pilot phase to debug the technical implementation, the main study was conducted for 12 days. We recruited five volunteers (students and researchers) from the University of Oulu to participate in the main study.

A notification was sent to each participant's mobile device between 8AM and 8PM at intervals between 60 and 90 minutes. The interval was randomized after every notification push. The notifications were sent to all users simultaneously, so the randomization took place for the whole participant pool, not for individual participants. In the notification, the participants were prompted to choose "yes" if they were willing to work on a task and "no" to indicate that they were not available for mobile work now (Figure 1). The user's choice was recorded by the application. Choosing "yes", the user was redirected to the online survey (on Google Forms), via the gateway that forwarded the users' location coordinates to the survey form. On this form, participants were instructed to pay attention to their current context and surroundings, and to consider if they would be willing to work on a task. We explicitly primed the users to assume a fair compensation for their work according to the local average hourly wage. Participation in the study was however not rewarded.

The questionnaire comprised four closed questions:

- Q1: *How long would you be willing to work on a task at this moment?*
- Q2: *What type of task would you be willing to work on at this moment?*
- Q3: *What method of data entry would you be willing to use at this moment?*
- Q4: *Would you be able or willing to ask opinions or input from friends, peers or other people around you for a task right now?*

The order of the answers for questions Q2-Q4 was randomised. The detected geographic location and the unique id of the participant was recorded as well. Based on our own estimates, filling in the questionnaire required less than 30 seconds of time.

We conducted open-ended and semi-structured interviews at the end of the study. We used the Critical Incident Technique [11] to identify and explore situations and settings in which the willingness of the participant to work on a task was particularly low or high.

Results

We sent out 680 notifications in total to the five participants' mobile devices during the main study. Each participant therefore received a maximum of 136 notifications at randomised intervals. Three notifications failed being delivered due to mobile phones being shut off. We recorded 133 clicks on the "yes" action button in the notifications, resulting in a click-through rate of 16.6%. Clicks on the "no" button were not tracked – an issue that we aim to address in future studies. We collected 71 responses to the questionnaire, indicating an overall response rate of 10.4%.

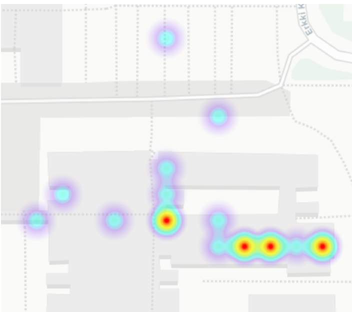

Figure 4: Heat map of locations on campus.

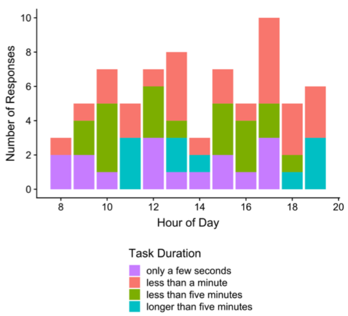

Figure 5: Task duration versus hour of the day.

Survey Results

Users clearly preferred short tasks over longer tasks (Q1; see Figure 3). Simple polls were an acceptable type of work in any context (Q2; see Table 1). Transcription and copywriting were the least preferred types of tasks. The preferred method of data entry (Q3) is correlated with this finding (Q3; see Table 2). When asking participants if they would consider involving others in the work, 53 (75%) of the responses were negative, meaning that they would not, or were unable to, involve other people to work with them in the current context (Q4). However, 14 responses were positive ("yes"), four "maybe", meaning that there is potential in reaching "small teams" at the same time for any tasks that could benefit from it.

To further understand how context influenced the above answers, we visually inspected the data by plotting maps and charts. Figure 4 depicts an overview of the locations on campus at which the participants were willing to work on a mobile task. We manually assigned labels (office, lab, walk-way, etc.) to the locations, based on our own knowledge of the campus. In Figure 4 we can observe that participants were most willing to work (or indeed simply spending most of their time, see Figure 7) at the offices, laboratory, and cafeteria. Investigating the raw data, we noticed a low willingness to involve others in tasks in the offices, with positive responses to this question in the shared, open plan laboratory and cafeteria.

Figure 5 maps the self-reported maximum task duration (measured by the number of responses to the questionnaire) by the hour of the day. The willingness to work on longer tasks is highest during the lunch break and after work. Regarding the type of task, participants were willing to spend the least amount of time on copywriting and transcription, which are the tasks that require the most amount of time (see Figure 6). Polls, data-related tasks (such as tagging, categorization, and cleansing), and moderation were significantly more popular than transcription and copywriting.

An analysis of the individual users revealed the personal preferences and different contexts of the participants. Figure 8 depicts an excerpt of the user analysis. While users 3 and 5 have similar preferences when it comes to working after office hours, users 1 and 5 spent their lunch breaks working on different types of tasks in different contexts.

Open-ended Interviews

While three out of five users reported that the frequency of the notifications was too high, two saw them as not being too intrusive, with the random intervals between notifications easing the burden on the users. After an initial phase of diligently responding "no" to notifications, all participants reported that they started to dismiss or ignore them if they were busy at the time of reception: "*when actively engaged with something, it is hard to pick up the phone and do secondary work*". One participant even responded that he "*saved the notifications*," knowing that he would "*be happy to work later on*".

The willingness to work on a task was highest during idle times, waiting times and periods of low-intensive work. "*Waiting for a doctor's appointment*" or at the bus stop were mentioned as good incidents for completing mobile work, while receiving a notification in times of focused work was distracting and annoying.

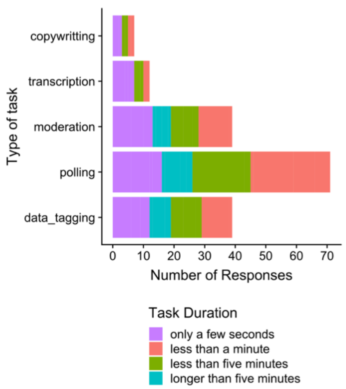

Figure 6: Task duration versus type of work.

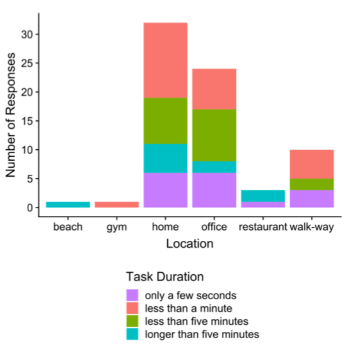

Figure 7: Task duration versus geographic location.

We noticed divergent responses when it comes to accepting work in different contexts. While one participant reported that he prefers to work on longer tasks at home after work, another user ruled out working after office hours, stating that "*after 4 PM, I felt reluctant in general, or weird, to be asked to do something* [work-related]".

Similar divergent responses were given about working on-the-go. One user reported that he would either dismiss notifications on-the-go or ignore them, while another user did not notice the notification in this context. Another user was happy to work on short tasks (mainly polls) while walking to locations.

Some participants were found to categorically reject specific types of tasks (e.g. transcription), regardless of their context. However, as one user stated, "*the reward would always influence my willingness at the end of the day. If the reward is worth it, I would consider it*". As for the monetary incentive, participants reported that "*if you paid* [the equivalent of my hourly wage]*, I would consider doing it in my spare time*".

The preferred method of data entry depends on the type of task, but also the context and the form factor of the device. Some methods of data entry are prohibitive in certain contexts, e.g. participants mentioned that they "*would not use the camera while on the toilet*".

Participants were willing to involve other people around them, but only if it was appropriate for the task and if the situation allowed it. One participant highlighted the educational aspects of solving tasks, stating that "*since I have a kid, I would have liked to involve him in some cognitive exercising*". Given the small sample size, we cannot discern a clear effect of the location on the user's willingness to collaborate.

Discussion

The interviews with the participants provided us rich qualitative insights. The participants favoured short polls over more complex types of work in any context, highlighting the preference for work that requires a comparatively low cognitive effort. The preferred methods of data entry correlate with this preference and are also influenced by the form factor of the used device.

We noticed divergent user behaviour patterns that underline the need for adapting notification schedules and work content to user-specific contexts, preferences, and individual mobile work patterns. Our study has shown that the context may indeed have a decisive influence on the user's willingness to work on a task and needs to be considered in context-aware mobile crowdsourcing applications. Even in our small-scale study, different user profiles and behaviour patterns started to emerge in the collected data and interviews. Our ultimate goal is to identify contexts on campus where people are receptive for microwork and to determine the optimal allocation of tasks to users given the users' current contexts.

In a future field trial on campus, we plan to embed tasks directly in the push notifications (or the application launched immediately following the notification), following the μEMA approach, to decrease the burden on the mobile workers. The efficient allocation of tasks to mobile users must consider the user's preferences, *e.g.* by building user models, and inferring the context from sparse information cues gathered from the user's mobile phone. Push notifications are not only a call-to-

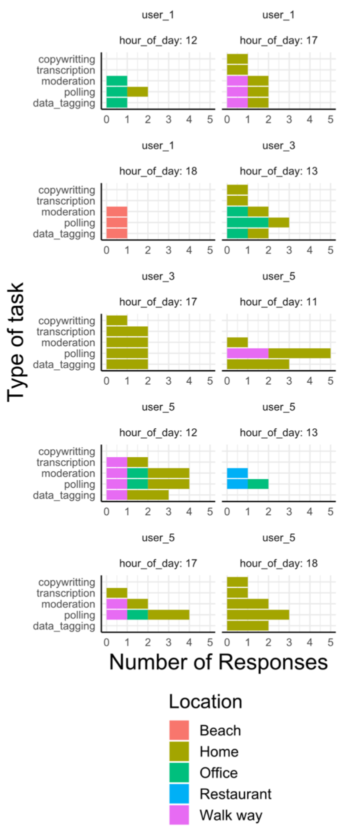

Figure 8: User locations and types of work at different times of the day.

action, but can be used to probe a person's willingness to work. As such, they can be used to learn about the contexts and to create preliminary user profiles. A task distribution system should however also let users pull tasks on their own volition.

Limitations
The participants' awareness of being studied could have affected their willingness to work on tasks. However, filling out the questionnaire can be considered as a task itself. We therefore estimate the willingness of a user to work on a task in a natural setting to be at least as high as self-reported. Further, due to the small size of the study and the biased selection of participants on campus, the results cannot be generalised to a broader population. For our purposes of deriving insights for informing a future field study, however, the qualitative results proved insightful.

Conclusion
We conducted a small-scale study investigating users' willingness to work on crowdsourcing tasks on their mobile phones, in different real-world contexts. Our qualitative analysis shows that the optimal distribution of tasks to mobile devices not only depends on the time of the day, but the rich contextual setting of the user as well as the users' personal preferences.

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