CrowdPickUp: Crowdsourcing Task Pickup in the Wild

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We develop and evaluate a new ubiquitous crowdsourcing platform called *CrowdPickUp*, that combines the advantages of mobile and situated crowdsourcing to overcome their respective limitations. In a 19-day long field study with 70 participants, we evaluate the quality of work that CrowdPickUp produces. In particular, we measure quality in terms of worker performance in a variety of tasks (requiring local knowledge, location-based, general) while using a number of different quality control mechanisms, and also capture workers' perceptions of the platform. Our findings show that workers of CrowdPickUp contributed data of comparable quality to previously presented crowdsourcing deployments while at the same time allowing for a wide breadth of tasks to be deployed. Finally, we offer insights towards the continued exploration of this research agenda.

CCS Concepts: • **Human-centered computing → Empirical studies in HCI**; • **Human-centered computing → Ubiquitous and mobile computing.**

Additional Key Words and Phrases: crowdsourcing, worker performance, local knowledge, location-based, tasks, ubiquitous crowdsourcing, mobile crowdsourcing, situated crowdsourcing.

ACM Reference format:
Jorge Goncalves, Simo Hosio, Niels van Berkel, Furqan Ahmed, and Vassilis Kostakos. 2017. CrowdPickUp: Crowdsourcing Task Pickup in the Wild. PACM Interact. Mob. Wearable Ubiquitous Technol. 1, 3, Article 51 (September 2017), 22 pages.
DOI: http://doi.org/10.1145/3130916

1 INTRODUCTION

Ubiquitous Crowdsourcing seeks to enable crowdsourcing work beyond desktop settings. There is a growing literature highlighting the advantages of ubiquitous crowdsourcing, such as targeting crowds of workers, and providing a richer (location-based) context during crowd work.

This work is partially funded by the Academy of Finland (Grants 286386-CPDSS, 285459-iSCIENCE), the European Commission (Grant, 6AIKA-A71143-AKAI), and Marie Skłodowska-Curie Actions (645706-GRAGE).
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DOI: http://doi.org/10.1145/3130916

Literature typically identifies two types of ubiquitous crowdsourcing: mobile crowdsourcing, and situated crowdsourcing [21]. Mobile crowdsourcing refers to collecting crowd contributions on mobile devices. On the other hand, situated crowdsourcing entails embedding input mechanisms (*e.g.*, public displays, tablets) in the physical spaces around us and leveraging users' serendipitous availability [32] or idle time ("cognitive surplus" [38]) to complete crowdsourcing tasks. Hence, situated crowdsourcing enables targeting specific groups of individuals with specialised knowledge (*e.g.*, creating keyword dictionaries that accurately describe the immediate surroundings of the deployed device [12]).

However, while the underlying ubiquitous technologies are substantially advancing, little work has systematically evaluated the quality of work that ubiquitous crowdsourcing produces. This is primarily hindered by the inherent limitations of each type of ubiquitous crowdsourcing: mobile crowdsourcing faces the barrier of requiring software installation on users' devices and need for promotion, while situated crowdsourcing does not allow for freedom of movement. Particularly, barrier of entry for new labour force has repeatedly been identified as a key challenge to mobile crowdsourcing markets (*e.g.*, [40]). If the markets fail to recruit active workers from certain geographic areas, it will be hard to efficiently provide labour in those areas because workers are reluctant to travel long distances for work [39].

Our work makes the following contributions to ubiquitous crowdsourcing:

- We present a system called CrowdPickUp that combines the advantages of mobile and situated crowdsourcing to overcome their respective limitations. CrowdPickUp, is an online crowdsourcing platform that can work with Android, iOS, Windows Mobile, and any other operating systems that support a standard browser. It allows workers to use their own personal devices, complete tasks regardless of place and time, and undertake tasks that require completion in a specific location (geofencing). Unlike previous mobile crowdsourcing deployments (*e.g.*, [1,26,42,43]), the platform is promoted through a situated crowdsourcing methodology using posters with standard printed QR codes and short URLs deployed in-situ. Our work demonstrates how a situated and technically simple to realise method can introduce a ubiquitous crowdsourcing platform to a constant stream of new workers and reach a substantial number of participants that had not participated in previous crowdsourcing efforts. While this approach has been validated in previous situated crowdsourcing deployments (*e.g.*, [13,17,18,20,21]), in our work we validate the efficacy of the approach when workers use their own personal devices instead of situated technologies to input their contributions.
- We systematically evaluate the quality of data collected in three distinct task categories (local knowledge, location-based, and general) in a large-scale field study using different parameters. Prior work on mobile crowdsourcing tend to build on one task type or only briefly mention the effects of types of tasks (*e.g.*, [24]). Furthermore, we employ three quality assurance strategies including a novel mechanism that considers time spent in a city as a means to improve the accuracy of local knowledge tasks, and collect qualitative data on workers' motivations, perceptions of the platform, and task preference.
- We compare the work quality that CrowdPickUp produced to literature, and show that workers of CrowdPickUp contributed data of comparable quality to previously presented crowdsourcing deployments, while at the same time offering a variety of different task categories and requiring minimal promotion.
- Based on our findings, we discuss recommendations for future ubiquitous crowdsourcing deployments with the aim of improving task uptake and the quality of gathered contributions.

2 RELATED WORK

Ubiquitous crowdsourcing has a growing research literature that typically extends traditional online crowdsourcing. We discuss previous research that influenced our work, focusing particularly on the two main types of ubiquitous crowdsourcing: mobile crowdsourcing and situated crowdsourcing.

2.1 Mobile Crowdsourcing

Mobile crowdsourcing is a major crowdsourcing paradigm that has been steadily gaining attention mostly due to the ubiquity of networked and feature-rich mobile devices. Using mobile crowdsourcing, it is possible to reach potential labour force practically anytime and anywhere. At the same time, crowds are more deeply engaged than ever with their mobile devices and can therefore become a source of data by gathering and sharing large amounts of data, such as capturing social events [44], providing in-situ weather reports [1], or giving real-time restaurant recommendations [1].

In recent years, a number of different mobile crowdsourcing platforms have emerged for different purposes. For instance, *mClerk* [16] is an example of a mobile crowdsourcing platform that allows users to receive tasks on their mobile phones via SMS, making the tasks accessible even to those with feature phones. Similarly, *MobileWorks* [33] provided employment to users of developing countries requiring them to complete Optical Character Recognition (OCR) tasks. The application divided documents into smaller pieces and sent them to different workers to address the limited screen resolution available on low-end phones. More recently, research has explored leveraging periods of user "downtime" to complete crowdsourcing tasks on mobile devices. As an example, Twitch Crowdsourcing [42] takes advantage of the common habit of turning to the mobile phone in spare moments to make crowdsourcing contributions. It offered a varied set of tasks, such as authoring a census of local human activity, rating stock photos, and extracting information from Wikipedia pages.

Mobile crowdsourcing is also suitable for tasks that required strong location specificity (*i.e.*, the task requires a crowd worker to physically visit a specific location). Alt *et al.* [1] explored location-based crowdsourcing using mobile devices for distributing tasks to workers. Their work focus on how workers may actively perform real-world tasks for others, such as giving a real-time recommendation for a restaurant, or providing an instant weather report in their current location. Similarly, Vaataja *et al.* [43] report a location-aware crowdsourcing platform for authoring news articles by requesting photographs or videos of certain events from its workers. *Askus* [26] is a mobile crowdsourcing platform with strong location specificity aimed at supporting collective actions and information capture. With Askus, users can contact other people in a certain geographical location and send them a request to carry out small tasks using their mobile phones. gMission [6] is yet another location-based crowdsourcing platform which features a collection of novel techniques including geographic sensing, worker detection, and task recommendation. The platform makes it possible to implement a new crowdsourcing mode (i.e., spatial crowdsourcing), in which a requester can ask for resources related to a specific location and a worker who is willing to take the task travels there to get the data. For location-based tasks, failure to recruit active users from certain geographic areas can lead to issues in efficiently providing labour in those areas since workers are reluctant to travel long distances for work. Travel distance has been shown to have effect on labour in city-scale deployments [39,40] and deployments within a single building/campus [24].

Furthermore, an active community has developed around the topic of crowdsourcing measurements and sensing. This participatory sensing movement is also referred to as "Citizen Science" [34] and relies on mobilising large parts of the population to contribute to scientific challenges via crowdsourcing. Often this involves the use of mobile phones for collecting data [3] or even donating computational resources while the phone is idle [2].

Finally, prior work on mobile crowdsourcing builds on one task type, or only fleetingly mention the effect of different type of tasks (such as in [24]). In our work, we compare three distinct categories of tasks: local knowledge, location-based and general tasks, and perform an in-depth analysis of workers' performance and behaviours.

2.2 Situated Crowdsourcing

Another increasingly popular crowdsourcing technique is using situated technologies (*e.g.*, public displays) to tap into a specific local labour supply. Situated technologies have certain desired characteristics for crowdsourcing, such as low barrier of entry for people who would not otherwise engage in crowdsourcing or targeting a specific group of wanted participants [11,18]. Humans are also naturally inclined to explore their environment and the technologies in an attempt to "kill time" [32], which can be exploited by offering the deployments to engage in locations where people typically have free time at their disposal. Unlike previous mobile crowdsourcing deployments (*e.g.*, [1,26,42,43]), our platform is promoted through a situated crowdsourcing methodology using posters with standard printed QR codes and short URLs deployed in-situ.

A recent example of a situated crowdsourcing deployment is *Umati*, an augmented vending machine used to explore *communitysourcing* [17]. Umati dispatched edible goods such as snacks and chocolate in exchange for labour that could only be completed accurately by local workers. Bazaar, by Hosio *et al.*, investigated how an economic market model applies in situated settings, concluding that the supply of labour can indeed be controlled with alternating the rewards also in situated task markets [18]. The same platform was later used to explore the collection of subjective and local data as well [13]. Two more recent examples include *CrowdFeedBack* and *CrowdButton* that together focus on sustaining the uptake and quality of unpaid crowdsourcing contributions [20]. As another example, City-Share facilitates efficient communication between official emergency personnel and volunteers in disaster zones by using public displays as communication hubs [30]. Recently, Huang *et al.* [21] proposed a genetic model inspired by the MIT's model on collective intelligence [31], aimed at identifying important contextual aspects for user contributions in situated crowdsourcing systems.

Despite the much-explored potential, situated crowdsourcing deployments are inherently limited by both scale and reach. Contrary to traditional online crowdsourcing, where a deployment can potentially reach billions of users [22] who contribute using their own familiar devices anywhere, in situated settings the workers typically complete tasks using devices deployed by third parties as part of the fixed environment. For this reason, researchers consider situated crowdsourcing more as an alternative, or different means of eliciting crowd contributions, rather than a replacement or competitor of online crowdsourcing [18]. Next, we introduce the developed system: CrowdPickUp. CrowdPickUp by design embraces the best qualities of both situated and mobile crowdsourcing, allowing people to discover and pick up tasks from their immediate environment using their personal devices and complete them later, whenever wherever.

3 CROWDPICKUP

Here we describe the design and implementation of CrowdPickUp -- a crowdsourcing web platform designed to run on any mobile web browser. Unlike typical mobile crowdsourcing deployments, there is no barrier to participation caused by the requirement to install dedicated software by the user. The welcome screen of the platform prompts users to create an account or login (**Fig. 1**).

Registration requires just a username and password, since a lengthy process can reduce participation when using ubiquitous technologies [18]. Upon login, users are shown the main screen in which they can select different types of crowdsourcing task categories. Additionally, users have access to a dashboard that shows a summary of their interaction with the platform (*e.g.*, number of total tasks completed, number of tasks completed in each category, number of coins generated). Users also have access to a web shop that allows them to purchase rewards with virtual coins earned by completing the tasks. Finally, a help screen provided users with information regarding the platform and how to claim their rewards.

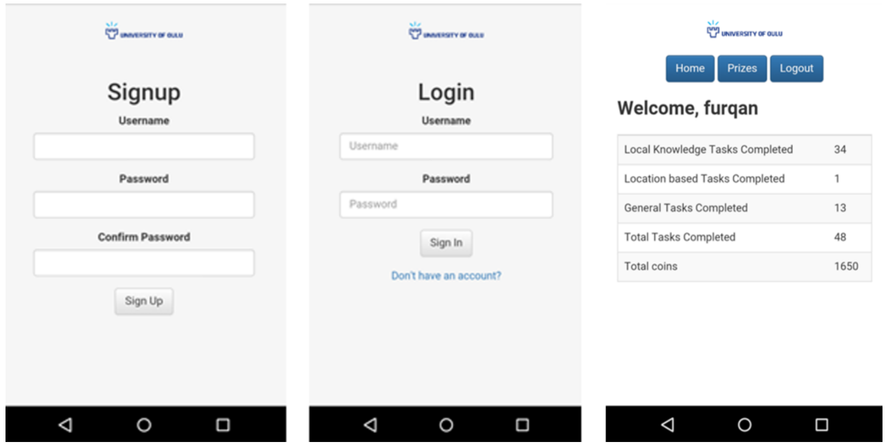

Fig. 1. From left to right: Signup screen, login screen, and user dashboard.

3.1 Technical Considerations

In the technical sense, the (front end / client side) platform was implemented using Bootstrap v3 (a popular CSS, HTML, and JS framework that is fully responsive, cross-browser compatible, and works with mobile and desktop devices of all sizes). Thus, while we did not explicitly test with more than a handful of browsers that the authors used during development, we expected no issues caused by browser incompatibilities. The server side is by design simple, as it requires mostly database queries. The server side scripts were implemented in PHP, and the platform was deployed on Amazon Web Services to maximize reliability. Further, we used HTTPS to provide secure communication between the client and the server side.

While a typical approach to mobile crowdsourcing is building dedicated native applications (*e.g.*, [1,26,42]), we chose the browser-based approach for a reason: a simple Web-based backend allows for a maximum compatibility across devices of all makes, models, and sizes, making the forecasted maintenance of the platform much less laborious than updating native applications as the underlying OSs evolve rapidly.

4 STUDY

We conducted a 19-day study to evaluate CrowdPickUp. Posters were placed at the notice boards throughout our university campus as well as bus stops in the city of Oulu (**Fig. 2**), and no further promotion was made. This follows the procedure of a typical situated crowdsourcing deployment that relies on serendipitous encounters and word-of-mouth promotion [11,18]. The advertisement poster of CrowdPickUp was an A3 sized page with the name of the platform at the top along with a small description. The poster also contained pictures of the prizes, and a shortened URL along with a QR Code. Both methods allowed participants to access the platform and thus the tasks. Finally, we added the logo of our University as previous work has shown that for data collection efforts it is important to build on reputation, which leads users to perceive the deployment more positively [28].

Fig. 2. One of the posters used during the deployment.

CrowdPickUp logged centrally all interactions, such as: accounts created, start and end time of each performed task (duration), responses for each task, and the amount of generated virtual coins. Participants could receive money (10€ or 25€ packs) or movie tickets in exchange for their virtual coins by visiting the web shop in exchange for 1000, 2500, and 975 virtual coins respectively (each virtual coin is worth 0.01€). After purchasing a reward, users were given instructions to email the researchers to schedule the pickup from a physical shop we had setup in our laboratory premises. We avoided direct conversions between virtual coins and money for simplicity (*i.e.*, few virtual for a few cents) and to encourage users to complete more tasks instead of rapidly cashing in [18].

4.1 Tasks

While most related work and earlier situated crowdsourcing deployments tend to focus on a single task, we designed four different task categories (Local Knowledge, Location-based, General, Survey). In two of these categories (Local Knowledge and General) there were three different subtasks, which we describe later. Upon successful submission of each task, the worker was awarded the payment in virtual coins (**Table 1**). The amount of virtual coins awarded was based on the estimated time and effort to complete each of the tasks. When skipping a task, no virtual coins were awarded. Our adopted price-setting follows contextual and cultural factors as suggested in previous work in ubiquitous crowdsourcing [18], instead of imitating the prices in online crowdsourcing markets (*e.g.*, Amazon's Mechanical Turk prices).

Table 1. Breakdown of the tasks in CrowdPickUp including task category, number of unique tasks available, worker input, and reward.

Category	**Task**	**Unique tasks available**	**Worker input**	**Reward (virtual coins)**
Local knowledge	Object translation	49	Text	20
	Hobbies in Oulu	36	Text	35
	Rate student housing	11	Likert-scale	50
Location-based	Rate locations	10	Likert-scale/text	250
General	Sentiment analysis	31	Multiple-choice	10
	Distance evaluation	29	Multiple-choice	10
	Word relevancy	27	Multiple-choice	10
Survey	Survey	1	Multiple-choice/text	300

4.1.1 Local Knowledge Tasks. In this category, workers required local knowledge related to their physical context (*e.g.*, knowledge of the city). We designed three tasks that all required different types of local knowledge. An example of each task can be seen in **Fig. 3**.

- **Object Translation:** To translate objects, workers needed to have a basic level of Finnish language skills. The task panel consists of an image of a fruit and the workers were asked to input the fruit's name in Finnish. A new image was loaded immediately as the worker either submitted or skipped the task.
- **Hobbies in Oulu:** Here, workers were required to provide knowledge of hobby opportunities in Oulu. The task panel consists of the name of a hobby (*e.g.*, swimming) and the worker was asked to describe if this hobby is doable in Oulu, and how (*e.g.*, when, where). As soon as the task was submitted a new hobby was loaded into the panel, allowing the worker to complete as many tasks as she wants in succession.
- **Rate Student Housing:** In this task workers were required to rate different student housing options across the city. The workers were asked to use a 5-step rating scale from "very bad" to "very good" (or "I don't know") to rate the following characteristics: cleanliness, nearby services, location, cost, Internet, and maintenance.

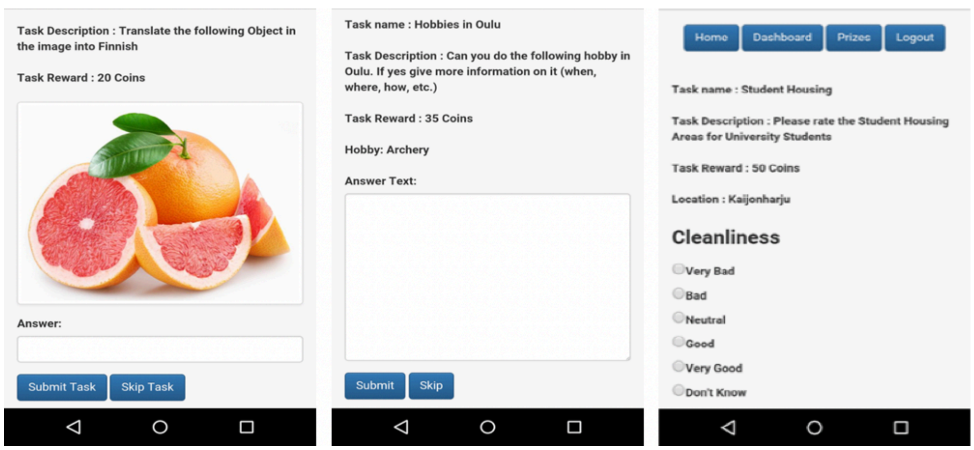

Fig. 3. Examples of each of the tasks in the local knowledge category.

4.1.2 Location-Based Tasks. In this category, workers were required to complete the tasks in a specific location. This was enforced in the design by allowing the tasks to be completed only if they were geo-located close enough to the physical address where a task was located. Technically we implemented this using the location API available in HTML5. Then we used Google Maps API to determine the distance of users to the address of a task upon submission, and if the user was not nearby, then they would be encouraged to relocate to the task location before being able to submit the task. After selecting one of the 10 available locations, the worker was shown the address and a picture of the location, and upon touching the image a map dialog box would appear with further navigation instructions. The workers were given the following assignments regarding the location:

- Rate the crowdedness of the place.
- Rate the noise of the place.
- Is there any good local food restaurant nearby, If yes then write the name.
- Rate the traffic situation of the place.
- Rate the available services of the place.
- Is the location easy to find.

The workers could select which tasks to complete (*i.e.*, which location to go to), and thus there was no need to implement any specific skip functionality. When completing a location-based task each of the assignments had to be answered. The assignments in each task were completed using a 5-step scale from "very bad" to "very good". An example location and the assignment screen (scrolled all the way down) can be seen in **Fig. 4**.

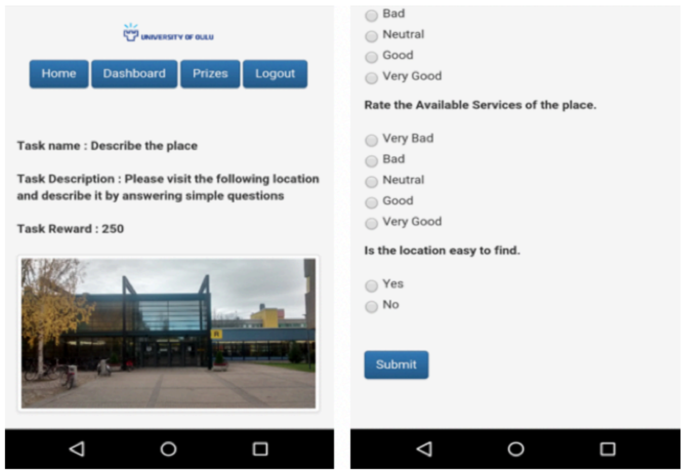

Fig. 4. Example of a task in the location-based category.

4.1.3 General Tasks. In this category, workers completed traditional crowdsourcing tasks that do not require local knowledge or the worker to be located in a specific area. Thus, the only requirement for the worker was to register an account on the platform. We offered the following tasks, which can also be seen in **Fig. 5**:

- **Sentiment Analysis:** This task was replicated from [10] and extended with more sentences. In this task workers were shown a text snippet to analyse. The sentiment options were: negative, neutral, and positive. We offered a mixture of straightforward sentences, *e.g.*, "I hate it when she acts like that" and challenging sentences that were formulated using factors that make sentiment analysis difficult for computers [7]:
    - *Context:* the content may have opposite meaning in a different context, *e.g.*, "The only downside of this restaurant is that it charges me too little for its service."
    - *Ambiguity:* the content contains a clearly positive or negative word, but still does not clearly express sentiment, *e.g.*, "Can you recommend a good tool I could use?"
    - *Sarcasm:* the sentiment of a specific word changes when the content is sarcastic, *e.g.*, "I'm so pleased road construction woke me up with a bang."
    - *Contronyms:* the content contains a word that changes sentiment depending on the language used. This occurs often in slang or other language variations, *e.g.*, "Their new album is so sick."
- **Distance Evaluation:** This task was replicated from [10]. In this task workers were shown pictures that contained 2 buildings marked with numbers 1 and 2. The assignment was articulated "Identify which building is closer to you". The choice was made using radio buttons and it was also possible to skip the picture.
- **Word Relevancy:** In this task workers were shown a sentence and three words. Then, the worker was asked to select one of the words as relevant to the sentence.

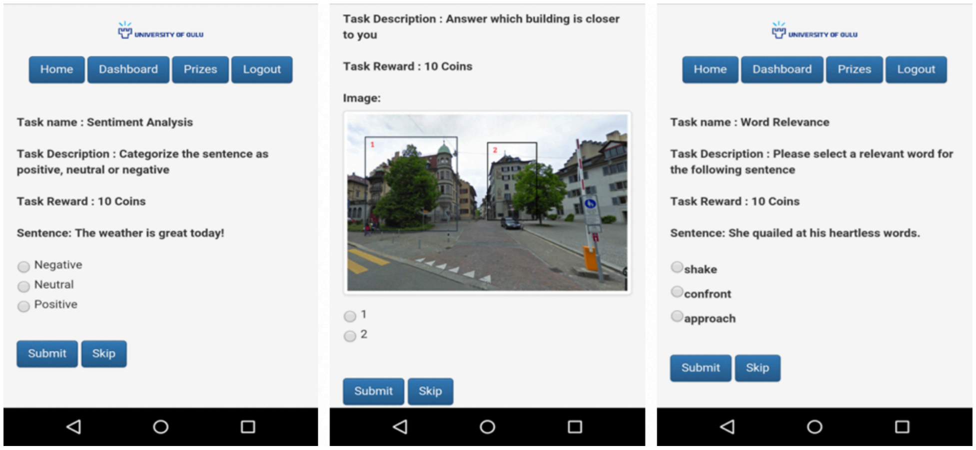

Fig. 5. Examples of each of the tasks in the general category.

4.1.4 Survey Task. The survey was a one-off task that workers could complete exactly once. It contained demographic questions (age, gender, years lived in Oulu, study degree & field, crowdsourcing experience) as well as open-ended items to collect feedback about the platform and the study.

4.2 Semi-Structured Interviews

We interviewed face-to-face users coming to collect their prizes. We held semi-structured interviews [35] based on a pre-drafted protocol that elicited their username, demographic information (in case these were not obtained in the survey), and commentary on themes such as:

- Main motivation behind participating in the study.
- Previous experience using crowdsourcing platforms.
- How they chose which tasks to complete.
- General thoughts on each task category.

5 RESULTS AND FINDINGS

During the study, 70 users registered to the platform, completing 6,693 tasks and skipping an additional 520 tasks. Participants generated 185,500 virtual coins of which 153,500 were used to purchased rewards (32,000 remained unused in the platform). The cumulative number of coins generated in each task category and in total, as well as number of coins redeemed can be seen in **Fig. 6**. Furthermore, **Fig. 7** shows the number of tasks completed throughout the course of the day in each task category and in general. **Table 2** and **Table 3** show the number of completed and skipped tasks (and percentages), the number of workers that completed at least one task, the number of workers that completed all tasks, as well as the accuracy and average time taken per task for the local knowledge and general task categories respectively.

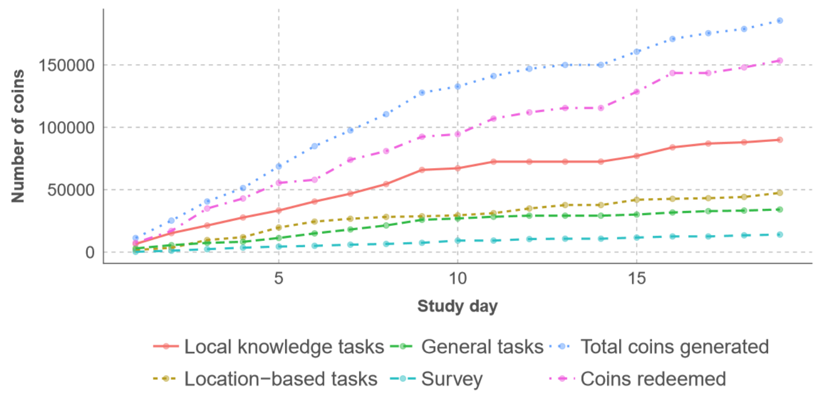

Fig. 6. Cumulative number of virtual coins generated in each task category and in total, as well as number of coins redeemed.

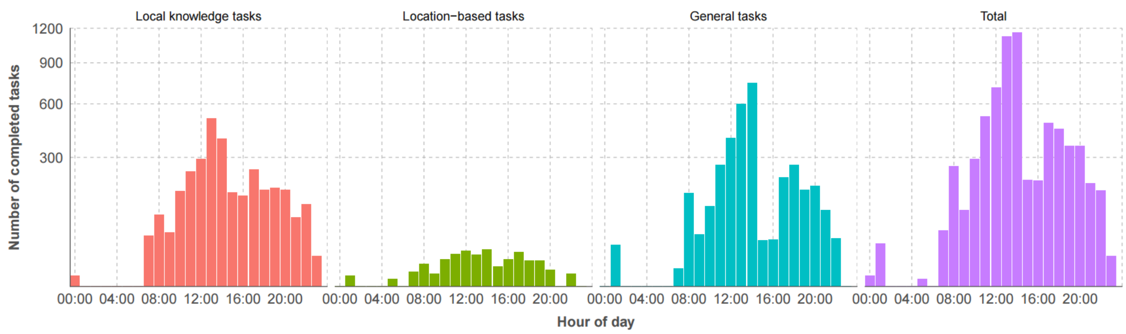

Fig. 7. Number of tasks completed throughout the course of the day for each task category and in total.

To determine the accuracy of contributions made to the task Hobbies in Oulu, we recruited 3 local knowledge experts (people who have lived in Oulu for over 15 years) to independently rate them as correct or incorrect. Fleiss' κ was run to determine the agreement between 3 raters' judgement on the accuracy of the contributions. There was substantial agreement between the raters, $\kappa = .795$ ($p < .001$). Majority voting amongst the raters was used to calculate the accuracy of this task.

Table 2. Descriptive statistics for the local knowledge task category.

Task	**Tasks completed**	**Tasks skipped**	**# of workers that completed at least 1 task**	**# of workers that completed all tasks**	**Accuracy (%)**	**Avg. time per task (s)**
Object translation	1634 (82.8%)	340 (17.2%)	49	6 (12%)	73.54	24.80
Hobbies in Oulu	1014 (91.6%)	93 (8.4%)	47	17 (36%)	68.54	29.53
Student housing	437 (91.4%)	41 (8.6%)	46	25 (54%)	-	23.95
Total	3085 (86.7%)	474 (13.3%)	-	-	-	-

Table 3. Descriptive statistics for the general task category.

Task	Tasks completed	Tasks skipped	# of workers that completed at least 1 task	# of workers that completed all tasks	Accuracy (%)	Avg. time per task (s)
Sentiment analysis	1356 (99.2%)	11 (0.8%)	50	37 (74%)	73.90	5.80
Distance evaluation	1236 (99.8%)	2 (0.2%)	48	38 (79%)	70.66	7.65
Word relevancy	826 (96.2%)	33 (3.8%)	39	21 (54%)	65.75	14.36
Total	3418 (98.7%)	46 (1.3%)	-	-	-	-

A total of 190 tasks were completed in the location-based category with each task taking 47.42 seconds on average. Out of the 42 participants that completed at least one location-based task, only 6 (14%) completed all tasks. In addition, 172 of these tasks included a suggestion of a good local nearby restaurant (43 unique restaurants). Given the subjective nature of both this task and the Student Housing task, we do not provide an accuracy analysis. Similar subjective tasks have been used in mobile crowdsourcing studies also in the past, in *e.g.* [24]. Theoretically, these types of subjective assessment tasks build on the averaged "wisdom" of the respondents, and the quality of the result is a direct function of volume of tasks completed [19]. Including different task types in the study, however, contributes to *task diversity* which is seen as important in studies of crowdsourcing markets [18,25]. To visually illustrate the differences in ratings for the locations in these tasks, we show the distribution of the Likert-scale responses in **Fig. 8** and **Fig. 9**.

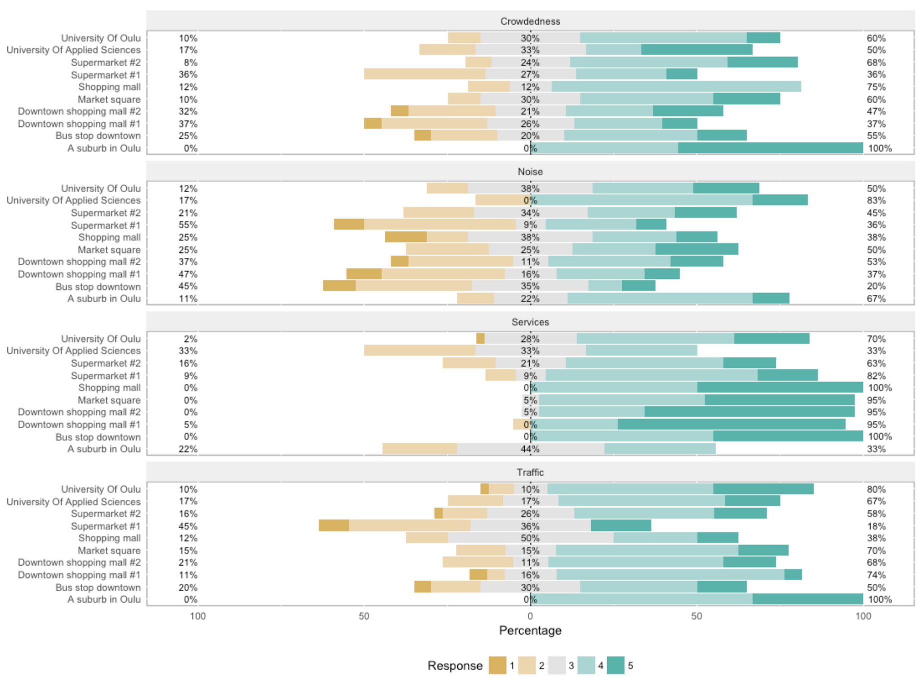

Fig. 8. Distribution of Likert-scale responses for the location-based task.

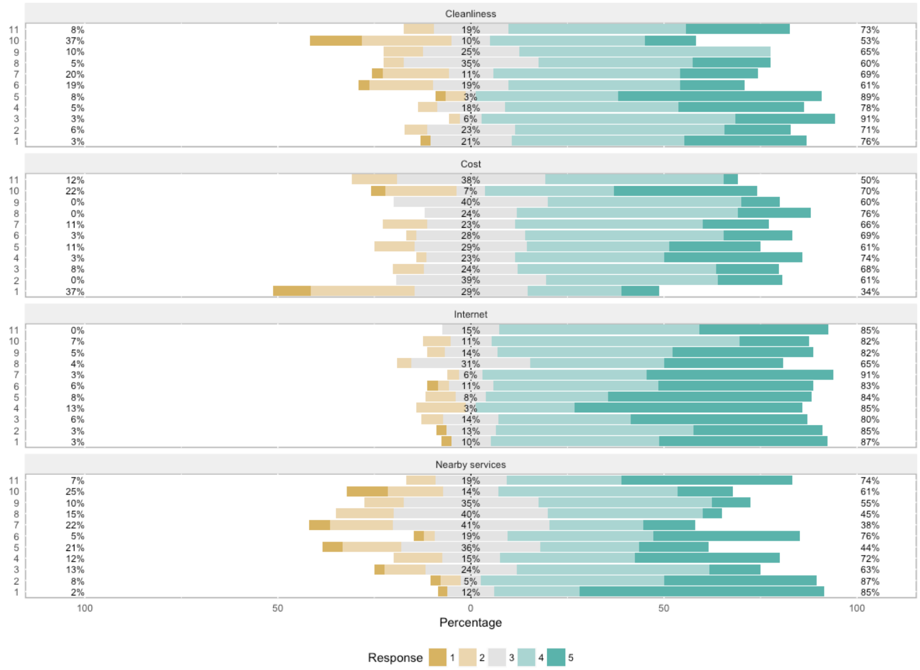

Fig. 9. Distribution of Likert-scale responses for the rate student housing task.

In terms of crowdsourcing effort measured in time spent completing the tasks, participants spent considerably more time with the local knowledge tasks (22.5 hours ~ 1,350 minutes) when compared to the general tasks (8.1 hours ~ 486 minutes). Participants spent 2.5 hours (~ 150 minutes) completing the location-based tasks, however this does not account for the time taken by the participants to travel and find the locations. Based on the results from **Fig. 6** we were then able to calculate the number of virtual coins generated per minute for these two task categories: 67 virtual coins per minute for the local knowledge tasks and 70 virtual coins per minute for the general tasks.

5.1 Workers' Performance and Participation Patterns

We investigated the performance of individual workers in different task categories. To do so, we selected a subset of workers (N=34) that made contributions to all 5 tasks that have ground truth. We then calculated and plotted the average accuracy of each worker in the local knowledge tasks and the general tasks (**Fig. 10**). Overall, workers performed better in the local knowledge tasks even though they took longer to complete. Upon further investigation, we found that time living in the city had a significant effect on these results. We separated the sample into 2 groups: 1) those that had lived in Oulu for less than 2 years, and 2) those that lived in Oulu for 2 years or more. There was a statistically significant difference in their performance in the local knowledge tasks (M=0.69, SD=0.12 vs M=0.80, SD=0.11; t(32)=2.54, p=0.02), but not in the general tasks (M=0.74, SD=0.11 vs M=0.69, SD=0.11; t(32)=1.13, p=0.27). We also compared workers' accuracy between tasks that had a visual stimulus (object translation, distance evaluation) and tasks that had a textual stimulus (hobbies, sentiment analysis, word relevancy), but found no statistically significant difference (p=0.57).

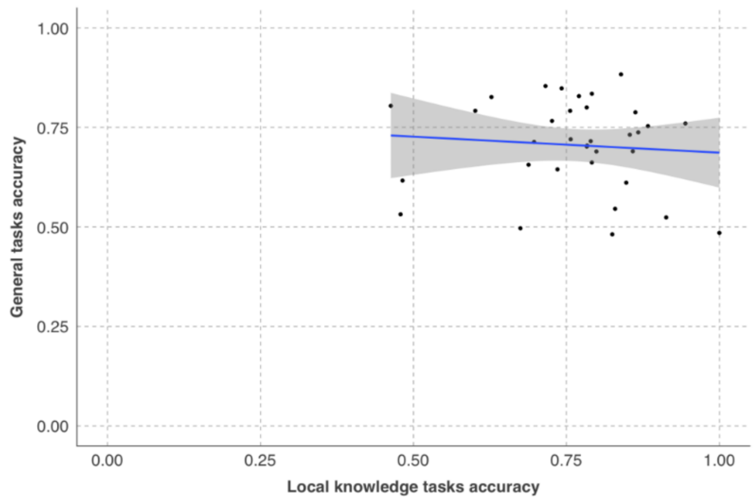

Fig. 10. Scatterplot comparing the performance of individual participants on the local knowledge and general tasks.

Furthermore, we explored the existence of different patterns of participation using two metrics: 1) Number of tasks completed, and 2) Time between first and last contribution (measured in days). After the removal of three outliers, we then clustered participants using the k-means clustering algorithm. Fig. 11 shows the three identified clusters:

- **Cluster 1 (Blue):** Participants that completed relatively few tasks in a short amount of time.
- **Cluster 2 (Green):** Participants that completed a relatively a high number of tasks in a short amount of time.
- **Cluster 3 (Red):** Participants that completed a relatively a high number of tasks throughout the study duration.

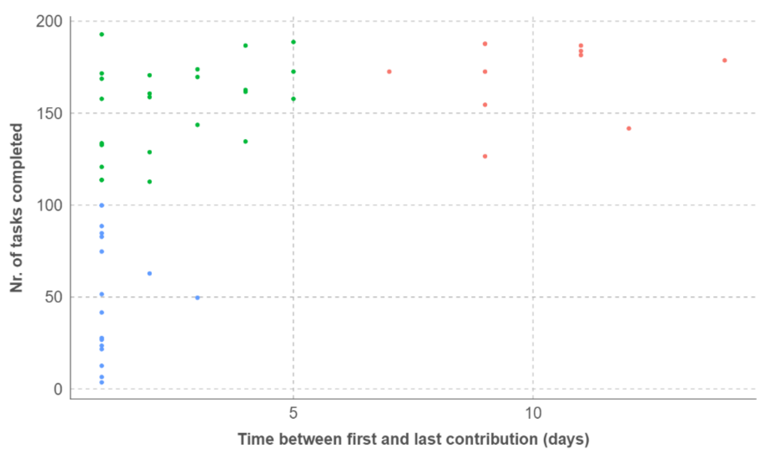

Fig. 11. Different clusters of participation patterns.

We then conducted independent samples t-tests to determine any differences between the clusters in terms of average accuracy. There was a significant difference (p=0.04) in the average accuracy of participants in Cluster 1 (M=77.7, SD=12.2) and Cluster 2 (M=69.2, SD=10.3). In addition, there was a significant difference (p=0.03) in the average accuracy of participants in Cluster 2 (M=69.2, SD=10.3) and Cluster 3 (M=75.9, SD=5.8). There was no significant difference in average accuracy of participants in Cluster 1 and Cluster 3. These results show that participants that completed a relatively high number of tasks in a relatively short amount of time performed worse than others.

5.2 Refining Data Quality

To improve the quality of the data generated by the workers, we employed three post-hoc quality control mechanisms, a typical procedure in crowdsourcing deployments (**Table 4**). For instance, we used agreement filters by analysing workers' agreement with each other in their answers. Such filters have been shown to be an effective quality control mechanism [4,13,23]. Here, we looked at individual tasks for which more than 50% of workers provided the same answer. Similarly, we also employed another common technique that involves removing poor-performing workers. We excluded workers that provided incorrect answers to more than 50% of their submitted tasks. In addition, we employed a mechanism catered specifically to the local-knowledge tasks: we only considered answers from workers that have lived in Oulu for more than 3 years (as indicated in the survey task). Finally, we also explored combinations of these mechanisms to optimise the accuracy of each task with the agreement filter coming last.

Table 4. Accuracy for each task using different quality control mechanisms.
Increase over unfiltered accuracy in parenthesis.

Task	**Unfiltered**	**Only workers living in Oulu for over 3 years**	**Removal of poor performing workers**	**Agreement filter**	**Only workers living in Oulu For over 3 years + Agreement filter**	**Removal of poor performing workers + Agreement filter**
Object translation	73.54	76.88 (3.34)	74.76 (1.22)	77.55 (4.01)	**85.71 (12.17)**	74.76 (1.22)
Hobbies in Oulu	68.54	72.99 (4.45)	78.29 (9.75)	83.33 (14.79)	86.11 (17.57)	**91.67 (23.13)**
Sentiment analysis	73.90	n/a	78.15 (4.25)	90.32 (16.42)	n/a	**96.77 (22.87)**
Distance evaluation	70.66	n/a	71.34 (0.68)	79.31 (8.65)	n/a	**79.31 (8.65)**
Word relevancy	65.75	n/a	73.51 (7.76)	85.19 (19.44)	n/a	**88.89 (23.14)**

We compare the accuracy obtained in each task of our study to the accuracy of previously reported crowdsourcing deployments. Similar to our analysis, the studies employed quality control mechanisms to improve the accuracy of the crowdsourced contributions. **Table 5** shows that tasks in our deployment obtained comparable accuracy levels to those reported in literature.

Table 5. Summary of performance in our study (rows 1–5, above the dotted line), and summary of previously published studies (rows 6–16, below the dotted line).

Task description	Stimulus	Worker input	Crowdsourcing type	Input technology	Accuracy (%)
Object translation	Image	Text	Mobile/Situated	Any device with a browser	74-86
Hobbies in Oulu	Text	Text	Mobile/Situated	Any device with a browser	69-92
Sentiment analysis	Text	Multiple-choice	Mobile/Situated	Any device with a browser	74-97
Distance evaluation	Image	Multiple-choice	Mobile/Situated	Any device with a browser	71-79
Word Relevancy	Text	Multiple-choice	Mobile/Situated	Any device with a browser	66-89
Sentiment analysis [11]	Text	Multiple-choice	Desktop	Personal computer	74
Distance evaluation [11]	Image	Multiple-choice	Desktop	Personal computer	70
Grade exams [17]	Text/Image	Numeric scale	Situated	Touch screen embedded on a vending machine	80
Count cells [11]	Image	Text (numbers)	Situated	Public display	40-90
Digitize text [16]	Image	Text	Mobile	Personal phone	76-93
Digitize text [33]	Image	Text	Mobile	Personal phone	89
Describe current location [13]	Current context	Text	Situated	Public display	80-90
Translation [8]	Text	Likert-scale	Mobile	Personal phone	75
Photo Ranking [42]	Image	Multiple-choice	Mobile	Personal phone	86
Structure the Web [42]	Text	Multiple-choice	Mobile	Personal phone	87
Situated Market [14]	Image/Video	Text and multiple-choice	Situated	Public tablet	81

5.3 Survey Results

Forty-seven participants (35 male, 12 female) completed the survey task. Age was recorded as a range choice: 4 participants were between 15-19 years old, 19 between 20-24, 15 between 25-29, 6 between 30-34, and 3 between 35-39. 10 participants reported having a high school or lower educational level, 14 a Bachelor's degree, 21 a

Master's degree, and 2 a Doctoral degree. As their major field of studies, 9 reported information technologies, 3 economic studies, 2 sciences, 16 engineering, 5 arts, and 12 other fields. Particularly relevant to the study is the time lived in Oulu. 8 of the participants reported having lived in Oulu for less than 1 year, 12 between 1-2 years, 7 between 2-3 years, and 20 over 3 years. Finally, the majority of participants (43, 91%) reported having no prior experience of working with a crowdsourcing platform prior to CrowdPickUp.

5.4 Interview Results

32 workers (22 male, 10 female) of the 70 who created an account in *CrowdPickUp* claimed prizes and were interviewed when collecting them. Their average age was 27.12 (SD=5.15).

The rewards were seen as an important motivator, particularly when completing tasks that the participants did not enjoy. The word relevancy task was mentioned (N=12) as a non-enjoyable task that participants either did not complete or powered through just to earn the virtual coins. For the location-based tasks, six participants (19%) reported enjoying going around the places, while others did not bother going to all locations for different reasons (*e.g.*, too far, location not part of their daily commute, etc.) even though it was the task with the highest rewards.

"Did it all in one evening, just bicycling around the city, going to places I don't usually go was nice."

"Brought a friend with me, he was catching Pokémon and I was completing the tasks, good exercise for both of us."

Another participant mentioned that he could see such location-based tasks being beneficial to the community.

"I can see the local tasks having an actual impact in the community, so maybe having more of these would be beneficial."

Overall, participants stated they felt that the local knowledge tasks were more interesting than the general tasks, and would have liked more of them as it gave them an opportunity to share knowledge on local topics.

"I wish you had more local [knowledge] tasks as these were more interesting to me."

"I would like more local stuff, maybe rate different bars to go, good places to visit, nice places to grab food."

However, within these local knowledge tasks the one pertaining to object translation was deemed quite challenging. Ten participants (31%) reported not knowing the lesser-known fruits and skipping tasks.

"Sometimes I knew it was a berry, just no clue which one."

"Looked like an alien to me, not a fruit so I just skipped it."

A common behaviour identified by the participants entailed using Google Translate or asking a nearby friend to figure out the name of the fruit in Finnish. Upon further investigation of our logs, we noticed that 26% of these tasks took over 30 seconds to complete suggesting that this behaviour was common amongst the participants.

"My Finnish is not perfect so I was googling for the translation tasks just to be sure."

"The ones I did not know I asked friends or tried to find them on Google."

The majority of the participants (N=25, 78%) reported learning about the platform from one of the situated posters and then deciding to try it out. There were exceptions, with seven (22%) participants reporting that their friends had told them about the platform and shared the link to access it.

"I was bored waiting for a friend, saw the poster and decided to give it a try."

"Passed by a poster one day, but did not have time to check it out. I remembered it though, so I came back later and registered".

Finally, four (12%) participants mentioned using their computers to complete certain tasks, particularly those that required more extensive typing (hobbies task).

"I used my computer to complete the hobbies task. Too difficult to complete on phone, I would just give shorter answers."

6 DISCUSSION

While online crowdsourcing is still the de-facto way to elicit crowd contributions, the popularity of ubiquitous crowdsourcing using mobile and situated technologies is growing. One of the main reasons behind this development is that ubiquitous crowdsourcing can circumvent certain limitations of traditional online crowdsourcing by, for example, collecting data from specific crowds and related to a surrounding context. The proliferation of ubiquitous crowdsourcing also stems from the fact that ubiquitous technologies, such as smartphones and public displays, have matured to allow users to contribute to crowdsourcing tasks on the go, thus enabling a wide range of different applications. In this paper, we design and evaluate a platform for ubiquitous crowdsourcing called CrowdPickUp. CrowdPickUp was designed to mitigate the primary shortcomings of both mobile crowdsourcing (*e.g.*, significant deployment effort by the workers and need for promotion) and situated crowdsourcing (*e.g.*, lack of freedom of movement), while offering different categories of tasks (local knowledge, location-based and general). To verify the feasibility of a platform with CrowdPickUp's characteristics, we evaluated the quality of work it produced in a 19-day field study that attracted a diverse set of 70 participants, the majority (91%) of which had never been involved in any crowdsourcing platforms beforehand, and showed that workers of CrowdPickUp contributed data of comparable quality to previously presented crowdsourcing deployments. Finally, through the discussion of our findings we offer recommendations for future ubiquitous crowdsourcing deployments with the aim of improving task uptake and quality of gathered contributions.

6.1 Task Performance

To reliably evaluate the quality of work that CrowdPickUp produces, we took certain crucial steps at the design stage and the analysis stage. In the design stage, we considered different task types that are afforded by the platform. This entailed designing tasks that can typically be found on many online crowdsourcing markets (*e.g.*, sentiment analysis, visual analysis), a location-based task that leveraged GPS capabilities of participants' mobile devices, and local knowledge tasks aimed at extracting information from people within this geofenced crowdsourcing environment. Furthermore, previous work has highlighted the importance of offering a diverse set of tasks to assure platform sustainability [18].

In the design stage, we also ensured that the tasks were sufficiently challenging. This meant designing the tasks with a certain degree of complexity. For instance, we included ambiguous sentences in the sentiment analysis task that require careful reading and appropriate comprehension. As another example, we purposely chose fruits in the translation task that are not widely known or can be easily mistaken for a similar one. This included fruits like *cherimoya* and *dragon fruit*, as well as a wide variety of different berries such as *boysenberries*, *gooseberries*, and *elderberries*. In fact, the translation task had the highest ratio of skips (17%) out of all tasks in CrowdPickUp, with 10% of the participants reporting not knowing the lesser-known fruits and skipping tasks.

In the analysis stage, we conducted an in-depth exploration of workers' performance and participation patterns. For instance, our results showed that time lived in the city had a significant impact on the accuracy of the local knowledge tasks, but not on the general tasks. This suggests that time spent within a certain geographical location will impact performance of tasks that require local knowledge. Future crowdsourcing deployments that have local knowledge tasks could consider only showing workers these tasks if they have lived in that specific geographical location for at least a certain period of time. As another example, our results showed that workers with different participation patterns performed differently. Those that completed a relatively high number of tasks in a relatively short amount of time performed worse than others. This suggests that these workers may have rushed through the tasks, which had an impact on the accuracy of their contributions. Given this finding, future crowdsourcing systems could limit the availability of tasks within certain time windows, especially for workers who have joined recently.

Furthermore, we employed three quality control mechanisms (as well as two combinations of these mechanisms), and compared the work quality to previously-published studies. It is common in crowdsourcing deployments to employ post hoc processing of the data to improve its overall quality [25]. In this paper, we leverage two commonly used techniques, agreement filters [4,23] and removal of poor performing workers [45]. We also introduce a novel approach that consider workers' performance in the local knowledge tasks, and entails filtering out workers who have not lived in the area for a certain period of time. The development of new quality control techniques that caters specifically to these new crowdsourcing paradigms is crucial to maintain adequate levels of work quality. Overall, these techniques proved effective in improving the quality of the contributions by 10-20%, particularly when used in tandem (**Table 4**). In addition, we find that the quality of work CrowdPickUp produced is comparable to previously published studies that used ubiquitous crowdsourcing. To strengthen this comparison, in our experiment we adapted two tasks from previous work on crowdsourcing using a desktop computer (sentiment analysis and distance evaluation tasks) [11]. In our study, the workers achieved similar accuracy results, which further highlights the feasibility of ubiquitous crowdsourcing platforms and reliability of the produced outcomes.

Another important aspect when considering performance in crowdsourcing deployments is the time taken to complete the tasks. When looking at Table 2 and Table 3 separately we can see that tasks that took longer to complete also had lower accuracy. Previous work has shown that task complexity has a significant effect on performance, both in terms of accuracy and time taken to complete the task [36], so this interaction between these two factors was to be expected. In terms of time taken by each task, the location-based tasks, unsurprisingly, took on average the most time to complete because it entailed multiple selections and text entry. Similarly, the hobbies and the student housing tasks took longer to complete than the general tasks because they required more extensive text entry or multiple selections. However, the translation task took an unexpected long time on average to complete, especially given the amount of input required. The reason for this became evident during our interviews as some participants stated using Google to find the correct answer and therefore took longer to complete the task. Conducting a crowdsourcing deployment in a geofenced environment increases the likelihood of participants having the expertise to appropriately complete local knowledge tasks [18]. However, this may not always be the case. Here, while in certain cases workers without the required expertise skipped the task, the majority sought the information, as it was easily obtainable, and learned the Finnish name in the process. This information seeking behaviour mostly occurred when workers knew the name of the fruit in their native language and just wanted to discover the Finnish term, and less so when they simply did not know what the fruit was. This was to be expected, since time is one of the main contextual factors in determining the likelihood of a person initiating and finalising their information seeking process [37]. Furthermore, this led to an unexpected outcome of our study, in which participants learnt about the local language while contributing data to the system. Finally, participants spent considerably more time completing the local knowledge tasks when compared to the general tasks (22.5 hours vs 8.1 hours). While the rewards for each individual local knowledge task were higher than the rewards for general tasks, workers gathered on average a similar number of virtual coins per minute when compared to the general tasks (67 vs 70 virtual coins gathered per minute of work). These results suggest that: 1) we effectively chose the rewards as to not bias participants to complete one task category over the other, and 2) even though the local knowledge tasks had a lower work to reward ratio, overall participants still reported wanting more local knowledge tasks and less general tasks as they found them more enjoyable.

6.2 Deploying Ubiquitous Crowdsourcing Platforms

During our interviews, participants reported that the local knowledge tasks were more interesting and would prefer these over the general tasks offered. However, tasks that required local knowledge were skipped more frequently and had less users completing all available tasks when compared to the general tasks. This can be explained by the fact that the knowledge required to complete the local knowledge tasks is much higher than the knowledge required to complete the general tasks. Participant preference of local knowledge tasks is predicted by the theory of psychological distance that suggests that people are more likely to engage in tasks that are "close" to them psychologically [27] as is the case with locally relevant tasks. This further highlights the importance of designing tasks that are contextually relevant for geofenced crowdsourcing deployments whenever possible, such as the one described in this paper. Many paid crowd work platforms do not provide sufficient task identity and significance. While tasks will not always have intrinsic value to the workers, as is the case in many paid crowd work platforms [25], there are direct payoffs when requesters convey the identity and significance of tasks to crowd workers [36], including worker perseverance and better quality results. In a geofenced crowdsourcing deployment, researchers could entice people to initiate participation by first introducing an intrinsically rewarding task, followed by a combination of both intrinsically rewarding and more mundane tasks when required.

As for the location-based tasks, some participants enjoyed completing them while others either completed only 1 or none at all as they were perceived to be too cumbersome. The use of location-based tasks that can offer important community benefits could lead to increased enthusiasm towards completing this type of tasks [15], such as reporting potholes within road network, identifying inaccessible spots in the city to those with physical disabilities, or reporting the conditions of local beaches and lakes. This would of course mean that other quality assurance mechanisms would need to be in place, such as asking users to upload photos of the location in addition to the GPS coordinate verification we used in our deployment.

Interestingly, by the end of the experiment 17% of the virtual coins were not redeemed. From an economics perspective, such unredeemed currency is known as "breakage" [9]. Breakage is considered a natural phenomenon, and contributes significantly to profits because it essentially means free labour. With digital labour markets this may also indicate a challenge for sustainability, especially if many workers leave their rewards unredeemed because they disappear from the system. In our platform, the payment model (bulk payment instead of micro-payments for individual tasks) likely contributed towards the number of leftover virtual coins in the system. Furthermore, it is important to note that the payment model can bias workers towards exhibiting certain behaviours, and researchers deploying crowdsourcing platforms should be aware of this effect.

Another important potential challenge in ubiquitous crowdsourcing platforms is reaching workers that are willing to contribute. A situated crowdsourcing methodology can help mitigate this issue as it has been shown to be able to reach untapped populations of workers that have never used any crowdsourcing platforms [18], which is supported by the results of our survey in which 91% of respondents reported not having any previous experiences with other crowdsourcing platforms. Furthermore, in situated crowdsourcing new workers are naturally attracted to the platform overtime [12]. While the situated posters used in this study may not be as inviting as public displays or kiosks used in previous work, they were still able to attract a sufficient number of users to our platform. Other promotion mechanisms, such as referral schemes [5] can provide additional motivation to promote an application, which could lead to an increased number of participants. On the other hand, referral schemes, such as the one reported in [5], typically entail a financial motivation for the referring, which can harm the sincerity of the recommendation [41], while this promotion happened organically in our platform.

Further, deployment of public displays and kiosks may not always be possible either for logistic, permission, or economic reasons, hence a mixed approach of using personal devices and situated promotion, similar to the one presented in this paper, may be more appealing. A potential variation of CrowdPickUp would entail the deployment of public kiosks that would allow people to complete tasks directly on them (*i.e.*, situated crowdsourcing), and then take tasks with them when they need to leave or when the task itself requires it. This would likely lead to a higher number of participants, but would incur higher deployment costs.

Regardless of the means, participation – as the key ingredient of sample size in any study – remains a challenge that researchers must always tackle, one way or another. In that sense, we argue, it is not a specific challenge to our platform, but to anyone conducting research without using the well-oiled labour markets, such as MTurk and CrowdFlower, where one can just pay to increase the uptake. In our case, while paper-based posters worked well in our study, there is clear room for improvements. In the future, we still plan to rely on situated promotion and recommend researchers developing mobile crowdsourcing platforms to do the same, as it has been proven to be effective in previous studies [*e.g.*, 12,17,18,20,30]. However, in addition to posters we are now exploring "curiosity objects", manufactured in a local FabLab, to better leverage serendipitous discovery and to communicate the possibility of becoming a worker, right there and right now. As another option, we have already gained access to a local interactive public display network, where we can embed the advertisements as interactive elements, or explore the concurrent use of situated public displays and people's personal gadgets in future studies with the platform.

6.3 Limitations

We acknowledge a number of limitations in the presented work. First, in order to contribute to CrowdPickUp, participants were required to have data connections on their mobile devices. While this is quite common in Finland, this may not be the case in other countries. Second, we assessed the quality of submissions through agreement filters, removal of workers with low-quality output, and number of years the participant has lived in the city. Other quality assessment methods such as asking participants to take a photo of their current location for verification purposes or using gold standards were not employed and could be further explored in future work. Third, while we rigorously tested different aspects that may have influenced worker performance (*e.g.*, effect of participation pattern, effect of task stimuli), other factors may have had an influence. For instance, previous work has shown that workers' cognitive abilities can impact their performance in certain crowdsourcing tasks [10]. Fourth, for the location-based tasks some of the rating options (*e.g.*, noise) may have been influenced by certain contextual factors (*e.g.*, time of day and day of the week). Since the task did not instruct participants to visit the locations at different times, we only provide an overview of the results due to insufficient data for certain periods. In addition, when calculating average time taken to complete tasks, we excluded tasks with null as the entry as these are a result of errors when saving to the database. Finally, we did not test all available types of crowdsourcing tasks (*e.g.*, article writing). We did, however, offer a wide range of tasks that we argue are sufficiently diverse to effectively evaluate the quality of work that CrowdPickUp produces.

7 CONCLUSION

In their seminal work, Kittur *et al.* [25] call for researchers to conceptualise new forms of crowd work that go beyond the simple, independent, and deskilled tasks that are common today in online crowdsourcing platforms. Ubiquitous crowdsourcing has the potential to pave the way for platforms to form the foundation of future crowd work by enabling a wider breadth of tasks that leverage ubiquitous technologies sensing capabilities as well as their strong location specificity. Here, we report on the development and evaluation of one such platform that combines the advantages of the two main types of ubiquitous crowdsourcing, mobile and situated, to overcome their respective limitations. We demonstrate that CrowdPickUp can produce work of comparable quality to previously presented crowdsourcing deployments given the use of appropriate quality control mechanisms, including a technique catered specifically to local-knowledge tasks. Our work extends the existing literature on ubiquitous crowdsourcing and provides important insights towards the continued exploration of this research agenda.

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Received February 2017; revised May 2017; accepted July 2017