An Empirical Study of Workers' Behavior in Spatial Crowdsourcing

Hien To*
University of Southern California, USA
hto@usc.edu

Rúben Geraldes*
National Institute of Informatics, Japan
rubengeraldes@gmail.com

Cyrus Shahabi
University of Southern California, USA
shahabi@usc.edu

Seon Ho Kim
University of Southern California, USA
seonkim@usc.edu

Helmut Prendinger
National Institute of Informatics, Japan
helmut@nii.ac.jp

ABSTRACT

With the ubiquity of smartphones, spatial crowdsourcing (SC) has emerged as a new paradigm that engages mobile users to perform tasks in the physical world. Thus, various SC techniques have been studied for performance optimization. However, little research has been done to understand workers' behavior in the real world. In this study, we designed and performed two real world SC campaigns utilizing our mobile app, called Genkii, which is a GPS-enabled app for users to report their affective state (e.g., happy, sad). We used Yahoo! Japan Crowdsourcing as the payment platform to reward users for reporting their affective states at different locations and times. We studied the relationship between incentives and participation by analyzing the impact of offering a fixed reward versus an increasing reward scheme. We observed that users tend to stay in a campaign longer when the provided incentives gradually increase over time. We also found that the degree of mobility is correlated with the reported information. For example, users who travel more are observed to be happier than the ones who travel less. Furthermore, analyzing the spatiotemporal information of the reports reveals interesting mobility patterns that are unique to spatial crowdsourcing.

Keywords

Spatial Crowdsourcing, Incentives, Mobility

1. INTRODUCTION

Crowdsourcing has been attracting extensive attention from the research community and the number of crowdsourcing services, e.g., ODesk, MTurk and CrowdFlower, is growing. Particularly, the ubiquity of hand-held devices opened up new opportunities for the crowd workers (workers for short) to perform tasks in the physical world using their mobile phones. This new paradigm has been referred to as *spatial crowdsourcing* (SC) [4] (a.k.a mobile crowdsourcing). Spatial crowdsourcing has been enabling new applications such as Waze, TaskRabbit and Gigwalk to become popular. Waze uses GPS-enabled mobile phones to collect real-time traffic information from workers while Gigwalk workers can check whether products are stocked in store.

Spatial crowdsourcing has been extensively studied in recent years. SC differs from online crowdsourcing since it involves worker mobility in the physical world. Thus, the workers and tasks are influenced by location-dependent factors, such as population density, worker mobility, worker co-location patterns. However, little research has been done to understand worker behavior in SC markets. In [6], the labor dynamics and mobility patterns of the workers in popular SC markets are investigated. The study in [8] reports on the motivations and experiences of individuals who regularly perform SC tasks by interviewing them. A recent study [9] provides some interesting results regarding the correlation between worker willingness (or reward) and travel distance. However, little study has been done on workers' behavior using real systems and users.

To fill this gap, in this paper, we studied the workers' behavior in two new paid SC campaigns in Japan. We developed an Android app named Genkii, to collect users' moods and we used Yahoo! Japan Crowdsourcing[1] as the payment platform. Any user could participate in the campaign by installing the Genkii app and creating a Yahoo! Japan account, through which they were paid. To receive a reward, a worker needed to use Genkii to report his/her mood (i.e., Happy, Ok, Dull) at a certain location and time. Subsequently, the participating users' behaviors were analyzed through spatial and temporal analysis.

Our findings in this study are three-fold. We first report the worker performance during the two campaigns. We obtained a total of 1059 reports from both campaigns, out of which 436 reports were from the first campaign and 623 reports from the second. We observe an "on-boarding effect" in both campaigns in which 40% of the users (with at least one report) made only one report. At the same time, 24% of the users are considered active, who made at least 10 re-

*These authors contributed equally to this work.

[1]http://crowdsourcing.yahoo.co.jp

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ports. We also observed a cyclic pattern in the number of reports per hour during a day. Particularly, 4, 12 and 20 are the hours with peak numbers of reports. Interestingly, they are pastimes in Japan. On the other hand, 1, 9 and 17 are the hours with the least number of reports. Not surprisingly, these are common commute times in Japan.

Second, we compared user participation in the two reward strategies (i.e., how well a user is retained in our 10-task campaign). Our analysis shows that the overall user participation decreases significantly in both campaigns, among which the drop rate is less in the increasing reward campaign. Particularly, the largest drop rate is between the first and the second reports (in particular, 50% of the users in the fixed reward strategy and 35% of the users in the increasing reward strategy). This result shows that workers are motivated by growing incentives to stay in the campaign. In addition, with the increasing reward campaign 17% of the users finish the 10-task campaign while this number is only 11% with the fixed reward campaign[2]. However, we found that rewards have a negligible impact on the reported moods.

Third, we study worker mobility from the reporting locations. We categorize Genkii users with at least six reports based on their mobility. Each worker has a certain degree of mobility defined as the area of the minimum bounding rectangle that encloses all the reporting locations, which is highly correlated with his/her commuting pattern. We observed that 75% of the workers travel within 500 square km. This result suggests that users tend to contribute data in the proximity of their homes. In addition, users are more likely to report Happy mood if they commute long distances named "Commuter" (up to 57%), while the ones who travel short distances, the so-called "House Dweller" have a large fraction of Dull reports (43%). Furthermore, by analyzing the co-location patterns of the user reports, we found six pairs of users whose reports are co-located at least three times. Interestingly, these user pairs have the same degree of mobility.

2. BACKGROUND

Spatial Crowdsourcing (SC) [4] is a type of online crowdsourcing where performing a task requires the worker to physically present at the location of the task. This new paradigm for data collection has been attracting attention in both research communities [6, 11, 12, 1, 10, 13] and industry such as TaskRabbit and Gigwalk. These platforms create a labor market in which individuals or corporations (i.e., requesters) can list tasks (e.g., requesting a picture at a particular location), and a specified reward for each task. A worker can then elect to complete a task against its deadline, and be compensated upon timely completion.

Incentives in Crowdsourcing: There has been a clear separation between intrinsic rewards (e.g., fun, compelling user-experience) and extrinsic rewards (e.g., monetary incentives). We focus on extrinsic rewards in this study. The relationship between the rewards and output has been investigated and shown to be complex. For example, higher rewards increase the quantity, but not the quality, of work performed by workers since the workers who are paid more consider the value of their work to be greater and thus are no more motivated than workers paid less [5]. Furthermore, although workers respond rationally to offered incentives, a non-trivial fraction of users appears to set earnings targets [3], e.g., total amounts evenly divisible by five since these amounts make good targets.

[2]These statistics were computed on a small sample of data.

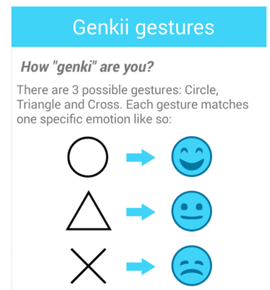
3. DESIGN OF OUR SC CAMPAIGN

In this section, we introduce our mobile application named Genkii for reporting users' moods and Yahoo! Japan Crowdsourcing as the platform for payment.

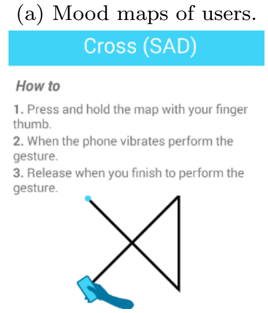
3.1 Genkii App

Genkii is a location-aware mobile app that enables a user to share his/her mood (i.e., Happy, OK, Dull). In our crowdsourcing campaigns, a *worker* is the owner of a mobile device with the Genkii app installed. Workers are supposed to report their own moods at a certain location and time, referred to as A *tasks*, through Genkii. In order to be rewarded a compensation (in Genkii points), a task need to be performed following guidelines discussed in Section 3.3. We will discuss how the app points can be directly translated into actual money in Section 3.2.

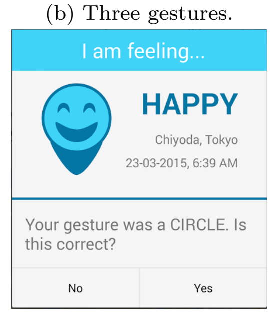
(a) Mood maps of users.



(b) Three gestures.



(c) Performing gesture.



(d) Confirming gesture.

Figure 1: Screenshots of Genkii app.

To make task reporting entertaining so that Japanese users are willing to share their locations, we implemented a physical gesture recognition as the main input method. Users report their moods by performing three different gestures as shown in Figures 1b and 1c. Circle gesture means "Happy"; triangle gesture represents an "OK" state while cross gesture denotes "Dull". After performing a particular gesture, users are required to verify if the gesture detected by Genkii is the intended one (Figure 1d). Users can correct the mood if the app fails to detect the input gesture.

Genkii uses a classifier implementing the extended Dynamic Time Warp (DTW) algorithm [7] to classify gestures. The physical gesture is measured by reading the accelerometer sensor raw data from the smartphone. When a user touches and holds the screen to perform a gesture, we start recording this raw data. When the user releases the screen, we stop recording and we feed the recorded raw gesture data to the DTW classifier.

3.2 Yahoo! Japan Crowdsourcing

We used Yahoo! Japan Crowdsourcing as the payment platform for our campaign and Yahoo! Japan's reward points as the compensation. The reward points given to the Genkii users are equivalent to Yahoo points, i.e., 20 Genkii app points equal to 20 Yahoo points. The Yahoo points can then be used to purchase many services on the Yahoo! Japan site. The points can also be directly exchanged with monetary value, i.e., 20 Yahoo points to 20 Japanese Yen. Yahoo! Japan Crowdsourcing also promotes our campaigns. Via this platform, our campaigns were instantly exposed to a large crowd of Yahoo! crowdsourcing workers who are already well-suited to perform crowdsourcing tasks.

3.3 Crowdsourcing Campaigns

To engage a larger audience in our crowdsourcing campaigns, we design a very simple task in which a user report his (or her) mood at a specific location and time rather than traveling to a specific location. We do not assign tasks to workers; instead, workers decide themselves to participate in a particular campaign as well as when and where to report. We rewarded reports only up to 10 times per user with the following conditions:

1. To avoid redundant frequent reports by a user at the same location and time, a report is counted as "rewarded" only if it is posted at least 4 hours after the most recent rewarded report. The other reports are considered as "non-rewarded".

2. To discourage spam reports, Genkii does not allow users to report consecutively at the same location. The distance from the current report to the last one must be greater than 100 meters.

3. To measure the level of user participation and due to our budget constraint, actual monetary rewards will be paid until a user achieves 10 rewarded reports. Each report can have different reward points.

The first campaign took place from June 19 to June 26, 2015 and implemented the fixed reward scheme (FR) while the second featured the increasing reward scheme (IR) from July 8 to July 15, 2015. FR has the same reward for every task while IR increases the reward per task over time as shown in Table 1 (i.e., average reward per task is 20 points). More concretely, the organizer posts 10 tasks for each campaign, each task includes title, description and links to the corresponding campaign. With the fixed-budget campaign, the organizer also sets a budget of $10 \times 200 \times 20$ points, each task is limited to the maximum of 200 users and each report worth 20 points. When the organizer receives 200 responses for a task from different users, Yahoo! Japan Crowdsourcing will close the task. This means that users can still report without receiving rewards.

By logging both rewarded and non-rewarded reports, our goal in the two campaigns is to capture insights about users' behaviors in SC from the reports, including the number of reports by workers over time, the accuracy of Genkii to relay truthful reports, the impact of rewards on user enrollment rates, and the worker mobility. Our hypothesis is that less number of workers joining IR campaign; however, they may stay longer in the campaign to achieve bigger and bigger rewards.

Reward	Task 1	Task 2	Task 3	Task 4	Task 5	Task 6	Task 7	Task 8	Task 9	Task 10
Fixed Rewards	20	20	20	20	20	20	20	20	20	20
Increasing Rewards	2	3	5	10	15	20	25	30	40	50

Table 1: Two reward schemes used in our campaigns.

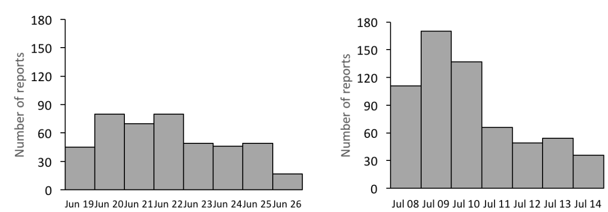
4. FINDINGS FROM THE CAMPAIGN

We report the results obtained from the two campaigns. Section 4.1 presents the worker performance in terms of the number of reports and the reporting accuracy with Genkii. Section 4.2 shows the impact of the rewards on task completion and reported moods. Section 4.3 provides insights on the overall mobility of the workers.

4.1 Worker Performance

4.1.1 *Number of Reports*

The first campaign with fixed reward scheme (FR) obtained 436 reports, 115 users installed the application, and 79 users provided at least one report. The second campaign with increasing reward scheme (IR) captured 623 reports, recruited 123 users, and 94 out of 123 users provided at least one report. Users reported their moods all across Japan.

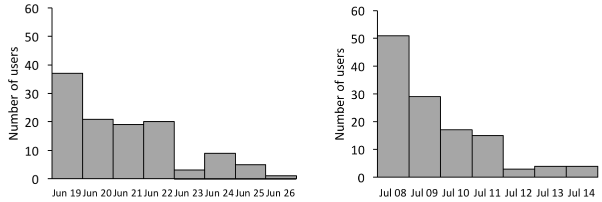


(a) Fixed reward (b) Increasing reward

Figure 2: Daily number of reports during campaigns.

Figures 2 and 3 show that both campaigns quickly took off. However, during the last four days, we observed a significant drop in the number of reports. Due to the 4-hour time constraint between two consecutive rewarding reports, it becomes harder to accomplish all ten tasks over time. It means that a long period of user participation is not easy to achieve.

We also analyzed individual user's performance from the number of reports by each user. In Figure 4, with FR campaign, we observed that 39 users (out of 79, so 49.3% of participants) made only one report while 18 users made at least 10 reports. It is expected that many users reported only once due to their curiosity of the app, not the SC campaign. However, with IR campaign, 30 users (out of 94, so 31.9%) made only one report and 24 users with at least 10 reports (Figure 4). These results show that IR made more users retained in the campaign to collect ten rewards.



(a) Fixed reward (b) Increasing reward

Figure 3: User acquisition throughout the two campaigns.

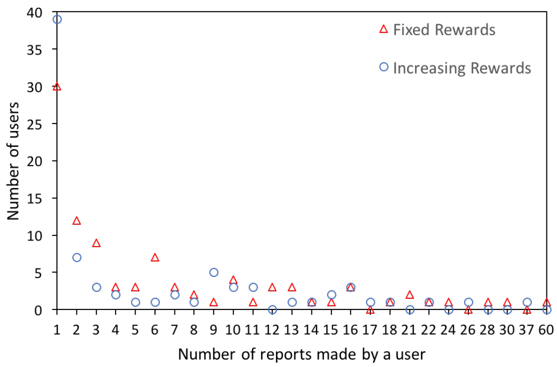


Figure 4: Number of reports made by users. In FR and IR campaigns respectively, on average each user contributes 5.5 and 4.1 reports with a standard deviation of 6.9 and 6.9 reports, the median is 2 reports in both campaigns.

Next, we analyze when people reported during a day. We used all 1059 reports from both campaigns. Figure 5 captures the hourly distribution of the reports, which clearly separates three 8-hour periods in a day. There seems to be a cyclic pattern during a day, with the lowest number of reports made around 1, 9, and 17 o'clock. Interestingly, we verified that these include common commute times in Japan. In contrast, a higher number of reports are recorded around 4, 12 and 20 o'clock. It is unexpected that the highest peak of reporting happened very early in the morning (at 4). This can be explained by the fact that many Japanese work at night and can be bored so they participate. And, meal times (at 12 and 20) seem to be the favorite times to report. We also observed that the peak times (4,12 and 20) coincide with the highest peaks of the "Happy" mood. After the peak hours, the number of "Dull" reports increases. The relative proportion of reported emotions seems not to vary much throughout the day.

4.1.2 Accuracy of Reports Using Gesture

This section reports the accuracy of Genkii reporting by detecting truthful moods from users' gestures. When a user performs a gesture, the app prompts the user to a YES/NO confirmation, e.g., "Your gesture was a CIRCLE. Is this correct?". It also worth to note that we do not have the ground truth of users' emotions (i.e., users can fake their emotions). Therefore, we did not take into account the quality of the responses but used the confirmed gesture as ground truth. That is, if the user selects YES, we consider this was the gesture the user wanted to report, so it counts as an accurately performed gesture. To measure the detection accuracy, we use the $\mathcal{F}$-measure, which indicates the harmonic mean of

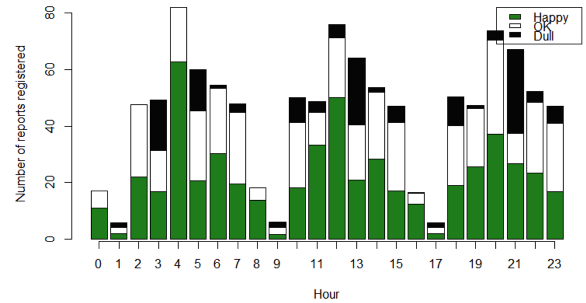


Figure 5: Distribution of reports over a day cycle.

Gesture	TP	FP	FN	Precision	Recall	F1-score
Happy	403	49	94	0.89	0.81	0.85
OK	365	61	39	0.86	0.9	0.88
Dull	97	53	30	0.65	0.76	0.7

Table 2: Accuracy of detecting gestures (both campaigns).

precision and *recall*. *Precision* is the ratio of true positives to all predicted positives, that is $\frac{TP}{TP+FP}$; *recall* is the ratio of true positives to all actual positives, that is $\frac{TP}{TP+FN}$. Thus, $\mathcal{F}$ depends on TP and FP. F-measure increases with high TP and low FP.

Table 2 compares the accuracy of detecting gestures in both campaigns. The result shows that F-measure for Happy and OK gestures (0.87 and 0.86, respectively) are significantly higher than the Dull gesture (0.77). This means that the Dull gesture is harder to correctly detect than the others. This is because the shape of cross gesture looks similar to the shape of triangle gesture (Figure 1c). This result suggests that we need to design gestures carefully to avoid such confusion. We also report the results for individual campaigns. The average F-measure is 0.85 for the first campaign, and 0.79 for the second campaign. We also measured the accuracy of the predicted gesture for the rewarded reports (85%) and the non-rewarded reports (84.3%). There seems not to be a significant difference between the two campaigns and between the rewarded and non-rewarded reports. Furthermore, we analyzed the campaigns to see if there is a relation between the number of accurate detections and the total number of reports made by a user. Our analysis finds no such relation, which suggests that accuracy of gesture detection has no impact on user retention in both campaigns.

4.2 The Impact of Rewards

4.2.1 Impact of Reward on Task Completion

The main goal of our campaign is to compare the effect of rewards on the user's reporting behavior. We used the user drop rate as a metric for how well the users retain in our 10-task campaign. The result is illustrated in Figure 4. In the fixed reward (FR) scheme, 18 users did at least 10 reports and 24 users performed at least 10 reports in the increasing reward (IR) campaign. In order to unlock a reward, the reports have to be made with a 4-hour interval since the previously rewarded report. Thus, considering rewarded reports only, we verified that 9 users completed the 10 rewarded reports during FR while 16 users finished the 10-task campaign with IR. We can conclude that users with

IR were more likely to finish the tasks (17%) in comparison with FR where only 11.3% of the users completed the 10 rewarded reports. This result confirms our hypothesis in Section 3.3. Hence, IR was more effective than FR. This conclusion is better illustrated in Figure 6.

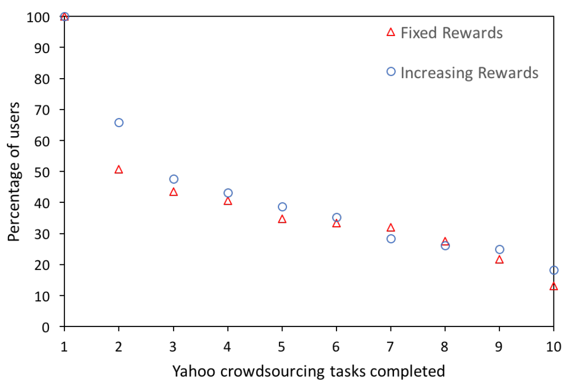


Figure 6: Comparison of the user drop rates between the fixed reward scheme and the increasing reward scheme.

It is interesting that all users submit the first report and the percentages of users who had more reports decrease quickly. There are two reasons why this is the case. The first reason is that the first report is always rewarded while the others have the 4-hours restriction in order to receive rewards. Another probable explanation is that steps required to obtain actual money are somewhat complicated for users. They first submit a report to obtain a code from Genkii app and then reimburse the code via Yahoo! Japan to receive money. To deal with such issues of user engagement, we can give higher rewards for the next tasks, remind users to report after four hours since their last reports, or integrate task reports and payment in a single app to remove an unnecessary burden from users.

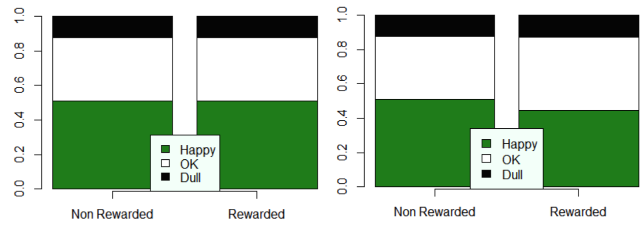
We also observed that 35% of all reports were non-rewarded, meaning that users reported within 4 hour gap period even though they were aware of the rule. This may be due to the use of gestures as a playful way to report, which suggests that careful design and game-like attributes can play an important role in keeping the users engaged.

4.2.2 *Impact of Reward on Reported Moods*

Overall, the mean proportion of registered emotions are: 49% of "Happy", 39% of "OK", and 12% of "Dull" reports. Considering all the reports obtained from the two reward schemes, we verified that reward does not seem to have an impact on the overall emotional reports captured (Figure 7). Particularly, Figure 7a shows that FR verifies the trend of slight differences in the overall emotional reports. With IR, however, we found that these differences were more accentuated the rewarded reports, displaying a higher "OK" percentage (Figure 7b).

4.3 Worker Mobility

As location-enabled emotional report application, Genkii provides insights on the overall mobility of the workers. To capture user mobility, we introduce the concept of "Genkii Territory" of a particular worker. Genkii territory is defined as the area of the minimum bounding rectangle (MBR) that encloses the locations of all the reports by a user.



(a) Fixed reward campaign (b) Increased reward campaign.

Figure 7: The rewards have a negligible impact on the proportion of emotions reported.

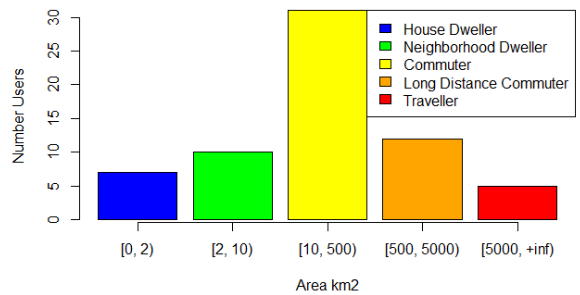


Figure 8: Genkii territory.

We calculated the "Genkii Territory" for 65 users (contributed a total of 886 reports) with at least six reports during both campaigns. We categorized the users according to their mobility as shown in Figure 8. The result shows that 75% users travel within 500 km^2. This property of Genkii territory was also referred to as "localness", in which users tend to contribute data in the proximity of their homes [2]. In particular, those who have a "Genkii Territory" that spans for less than 2 km^2 are called "House Dweller". If they have a territory no larger than 10 km^2, they are classified as "Neighborhood Dweller". Most users have Genkii territory between 10 km^2 and 500 km^2. These values could be common for "Commuter". We also defined a "Long Distance Commuter" category for the users who have "Genkii Territory" between 500 km^2 and 5000 km^2 and "Traveller" label for the users with territory area larger than 5000 km^2.

Figure 9 shows the average number of reports per user. Interestingly, the result suggests that the users in the "Traveller" group report as twice as the other groups while the users in "House Dweller" are less willing to report. It is due to the spatial constraint that a user cannot have two consecutive reports at the same location. More specifically, he can report if his current location is at least 100 meters away from the location of the previous report. Thus, users who are more willing to travel have more opportunity to report.

To understand the relationship between the degree of mobility and the users' overall emotion, we computed the proportion of registered emotion for each group in Figure 10. As expected, the users in the "Dwellers" groups, who travel in short distances, shows the largest fraction of Dull reports (i.e., 43% for "House Dweller") and the smallest percentage of Happy reports (34% for "House Dweller" and 35% for "Neighborhood Dweller"). On the other hand, the users who commute longer distance have a higher fraction of Happy reports (e.g., 57% in "Long Distance Commuter"). This can be explained by common sense that most people are excited

User1	User2	R1	R2	MBR1	MBR2	Times
U219	U105	24	16	9.0	7.7	7
U266	U256	10	10	248	193.2	4
U118	U162	22	11	686.5	1254.8	4
U226	U164	13	11	3.2	9.4	3
U232	U163	12	26	361.8	301.9	3
U241	U107	13	16	15.5	75.8	3

Table 3: Genkii territory of the collocated users. The last column represents the number of co-locations. R1, R2 are the total number of reports for each user. The unit of MBR is km^2.

when traveling, which is often interpreted as happy. On the other hand, many people feel bored when staying in the same area for a long time.

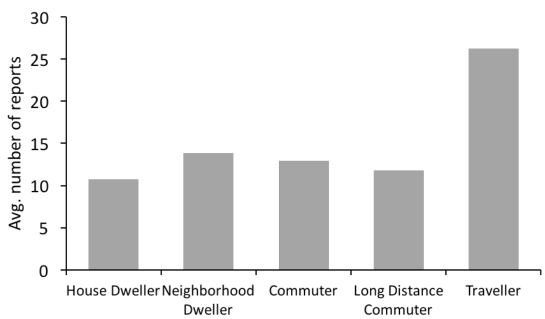


Figure 9: Average number of reports per user.

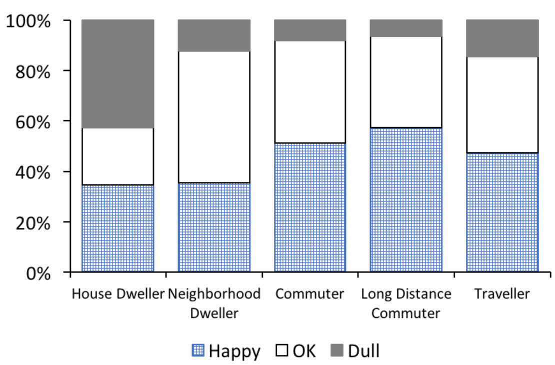


Figure 10: Mood distribution per degree of mobility.

Finally, we report the co-location patterns of the user reports. If two users have reported at the same location (e.g., the reports are within 100 meters from each other), they are spatially connected in geosocial networks. We found six pairs of users whose reports are co-located at least three times (Table 3). Particularly, these user pairs are in the same "Genkii Territory", which infers that if two users' reports are collocated, they tend to travel in the same territory (or have the same degree of mobility). Furthermore, these users are active since they all made more than 10 reports.

5. CONCLUSIONS

This study provided an exploration of real SC workers' behavior in several aspects: the worker performance, the impact of reward on workers' participation level, and workers mobility. In particular, by analyzing the frequency of one-time reporters, we observed that the fixed reward campaign attracts more of these users than the increasing reward campaign. However, the increasing reward campaign encourages users to perform more tasks by starting with a lower reward and increasing the reward over time. Furthermore, the reported data plausibly explains the trends and cultural aspects, e.g., users are least likely to participate in a campaign during commute times in Japan. In this study, we considered monetary reward only; thus, as a future plan, we will include other methods to keep the users engaged, such as gamification of crowdsourcing.

6. ACKNOWLEDGMENTS

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