Complete Research Report

Exploring Incentive Mechanisms for Mobile Crowdsourcing

By

Jurairat Phuttharak

April 2019

Contract No. TRG6080015

Complete Research Report

Exploring Incentive Mechanisms for Mobile Crowdsourcing

Jurairat Phuttharak
Prince of Songkla University, Trang Campus

Sponsored by The Thailand Research Fund (TRF)

Content

Abstract

Project Code : TRG6080015

Project Title : Exploring Incentive Mechanisms for Mobile Crowdsourcing

Investigator : Jurairat Phuttharak
Prince of Songkla University

E-mail Address : jurairat.b@psu.ac.th

Project Period : 2 years

The rapid adoption of mobile devices enables capture and transmission of a variety of sensor and user-contributed data, creating a new data collection paradigm and a wide range of services, often termed as mobile crowdsourcing. However, we are still investigating factors contributing towards the effectiveness of such systems. One key factor to succeed in mobile crowdsourcing applications is the incentive mechanism, which motivates people to contribute to a crowdsourcing effort. In this research, we conducted field experiments that compared the effectiveness of non-monetary and monetary incentive mechanisms, using both quantitative and qualitative methods. The focus was on an exploration of how these mechanisms motivate users' performance in a mobile crowdsourcing environment. In the experiment, we developed a smart zoning application that allows users to share areas of the cities they perceived as safe or unsafe. The results from this study contributes to research in mobile crowdsourcing for urban understanding. Taken together, these results suggest that payment-related incentives can not only engage people's interest in project participation but also help improve their work performance in terms of productivity and quality. Notably, a fixed-price financial reward mechanism is best suited for short period data collection and achieving data quality. Also, referral incentive mechanisms, if properly designed, have the potential to extend user coverage, both spatially and temporally. These results can be helpful with regard to the formulation of guide- lines on how to create and organize effective payment-based incentives for crowd involvement in cities.

Keywords : Mobile Crowdsourcing, Incentive Mechanisms, Crowdsourcing

บทคัดย่อ

รหัสโครงการ : TRG6080015

ชื่อโครงการ : Exploring Incentive Mechanisms for Mobile Crowdsourcing

ผู้วิจัย : Jurairat Phuttharak
หน่วยงาน: Prince of Songkla University

อีเมล : jurairat.b@psu.ac.th

ระยะเวลาโครงการ : 2 ปี

ด้วยเทคโนโลยีที่พัฒนาอย่างรวดเร็ว ทำให้อุปกรณ์สื่อสารเคลื่อนที่แบบพกพาสามารถตรวจจับข้อมูลต่าง ๆ ผ่านเซ็นเซอร์ที่อยู่ภายในอุปกรณ์ได้หลากหลาย ทั้งนี้ผู้ใช้มือถือในปัจจุบันยังมีส่วนร่วมในการสร้างเนื้อหาข้อมูลได้ด้วยตัวเอง เกิดเป็นบริการรูปแบบใหม่ ๆ ขึ้นมากมาย ซึ่งการใช้คุณลักษณะพิเศษของอุปกรณ์สื่อสารเคลื่อนที่ดังกล่าวเรียกว่า Mobile Crowdsourcing ปัจจุบันนักวิจัยยังคงศึกษาปัจจัยที่ส่งผลต่อประสิทธิภาพของระบบ Mobile Crowdsourcing โดยปัจจัยที่สำคัญที่ทำให้โปรแกรมประยุกต์ของ Mobile Crowdsourcing ประสบความสำเร็จคือ การสร้างแรงจูงใจ (Incentive mechanism) เพื่อให้ผู้คนเข้ามามีส่วนร่วมในระบบดังกล่าว ในงานวิจัยนี้เราได้ทำการทดลองเพื่อเปรียบเทียบกลไกสร้างแรงจูงใจใน 2 ลักษณะ คือ แรงจูงใจที่ไม่มีค่าตอบแทน และ แรงจูงใจที่มีค่าตอบแทนเป็นเงินรางวัล โดยทำการวิจัยทั้งเชิงปริมาณและคุณภาพ โดยเน้นไปที่การทดลองเปรียบเทียบ กลไกสร้างแรงจูงใจที่มีผลต่อสภาพแวดล้อมของระบบ Mobile Crowdsourcing ในหลาย ๆ วิธี โดยงานวิจัยได้พัฒนาโปรแกรมประยุกต์ Crowdspots เป็นกรณีศึกษาเพื่อให้อาสาสมัครที่อาศัยในพื้นที่ที่ทำการวิจัยได้เข้ามาแชร์รูปภาพ และกำหนดพิกัดในแผนที่ว่าเป็นจุดเสี่ยงภัยหรือจุดปลอดภัย ผลของงานวิจัยสรุปได้ว่า การใช้แรงจูงใจที่มีค่าตอบแทนเป็นเงินรางวัลจะดึงดูดให้ผู้คนเข้ามามีส่วนรวมในการทำกิจกรรมของ Mobile Crowdsourcing และยังส่งผลต่อปริมาณงานและคุณภาพของชิ้นงานที่อาสาสมัครได้มีส่วนร่วมในกลไกดังกล่าว
นอกจากนี้ผลงานวิจัยยังสะท้อนให้เห็นว่าการใช้เงินรางวัลในลักษณะ fixed-price เป็นแรงจูงใจที่เหมาะสมที่สุดในช่วงเวลาที่ทำการทดลอง ทั้งในเรื่องปริมาณชิ้นงานที่มีส่วนร่วมและคุณภาพของชิ้นงาน ขณะที่การใช้กลไกแรงจูงใจแบบ referral มีผลดีในกรณีที่ต้องการเก็บข้อมูลให้กระจายให้พื้นที่ที่ต้องการ (coverage) ผลของงานวิจัยนี้จะเป็นแนวทางสำหรับการสร้างแรงจูงใจในระบบ Mobile Crowdsourcing ได้อย่างมีประสิทธิภาพ

คำสำคัญ : Mobile Crowdsourcing, Incentive Mechanisms, Crowdsourcing

Output จากโครงการวิจัยที่ได้รับทุนจาก สกว.

Phuttharak, J., & Loke, S. (2019). Exploring Incentive Mechanisms for Mobile Crowdsourcing: Sense of Safety in a Thai City. International Journal of Urban Sciences. doi: 10.1080/12265934.2019.1596038.

1. Introduction

There has emerged a new computing approach that employs human abilities to perform the tasks combined with machine computation. This new mode of human involvement with machine is called *crowdsourcing*. Crowdsourcing is an approach to outsourcing tasks to be carried out by crowds reachable through the Internet. Examples of such tasks are those related to the areas of sentiment analysis, natural language understanding, image recognition and creativity [1, 2]. These kinds of tasks require high accuracy and efficiency. Although many previous studies have focused on increasing the performance of machine-based computational systems and using sophisticated algorithms and computing architectures to solve complex problems, there are a large number of tasks that currently cannot be accurately and efficiently performed by machines [3]. These tasks are better suited to humans who are innately good at creativity, visual processing, planning, and analysis tasks. Hence, humans can perform them easily with high accuracy and efficiency. Recently, the rapid diffusion of crowdsourcing technologies has been seen both in industry as well as in the academia [4]. Large companies exploit the benefits of crowdsourcing such as seeking ideas from the crowd. Dell[1] gathered ideas from various groups of people, either inside or outside their company, to make a good decision on how to design their new products to most satisfy the future customers. Other examples of the similar exploitation are particular cases of the well-established firms that include Threadlesss, iStockphotos, and InnoCentives.

The applications of crowdsourcing are not restricted only to business, but it can also be applied to the areas of scientific research and engineering, such as volunteered geographic information [5], the cultural heritage domain [6], and the public health ecosystem [7]. Notably, a growing segment of mobile phones is turning to ubiquitous computing. Mobile phones are increasingly able to sense a variety of modalities; for example, the mobile devices recording text, images, and location information. It is referred to as participatory sensing, when users are involved in deciding what data to collect. In recent years, mobile crowdsourcing applications have emerged and become a potential device for business and society [8], and for smart cities [9]. Sensing applications using crowd-powered computing [10] [11] [12] [13] are designed for monitoring purposes in different situations, such as monitoring movement patterns (e.g., running, walking) in common activities and monitoring traffic congestion and air pollution levels in an intelligent transportation system of smart cities.

The deployment of crowdsourcing applications in the real world faces several challenges such as power consumption related to the extra burden of sensing and transmitting, user's location privacy concerns, and integration of sensing information from different sources types [14] [15] [16]. However, the success of crowdsourcing applications depends on the number of participating users. Sustainability of a crowdsourcing application also depends on the volume of consistent users' participation. Thus, it is important to ensure that necessary elements with the abilities to attract and sustain users' participation are embedded into the crowdsourcing applications. One of these elements is an incentive or motivation. Incentive mechanisms are considered as necessary to increase user participation in a crowdsourcing task. To be attractive and appealing, the incentive mechanism has to be designed according to users' preferences.

The incentive mechanism is the recruitment strategy which requires users to con- tribute to crowd tasks in crowdsourcing systems. Doan et al. [17] discussed crowdsourcing systems on the web from a variety of perspectives. They introduced the nature of collaboration on crowd contribution in two aspects: internal factors, such as learning and boredom, and external factors like the provision of monetary interventions. Monetary incentives were found to be the most important factor for participation in the software development crowdsourcing domain [18]. Much work [19] [18] [20] has suggested that workers perform better when offered performance-contingent financial incentives.

In this research, we investigate the use of incentive mechanisms based on the monetary approach, comparing it with non-monetary approaches. The question of whether different incentive mechanisms impact upon users' decision on working tasks using mobile crowdsourcing applications are addressed. We consider micro payment models with different set amounts per sample and referral-based payment models with low and high levels of such incentives for direct referrals. These incentive schemes are com- pared to the base case of no additional incentive mechanism for the data collection as a whole. We define a set of metrics that can be used to evaluate the effectiveness of incentives and report findings derived from a pilot study using various monetary incentive mechanisms in sustainable smart city crowdsourcing applications.

In particular, our application involves crowdsourcing feelings of safety about CBD locations in a Thai city. Thai people may not be familiar with the term "crowdsourcing", but they may actively engage with its process in their daily life activities; e.g., sharing the files, video clips or even their ideas/opinions via social media [21]. In the study, we also discuss both quantitative and qualitative evidence on the effectiveness of the different motivations and strategies. The results contribute to the area of mobile crowdsourcing by proposing the design guidelines and mechanisms on how to create and organize effective payment-based incentives with crowd involvement.

2. Objectives

- To investigate the use of incentive mechanisms based on the monetary approaches (micro-payment and referral-based payment model) comparing with non-monetary approach.
- To compare various incentive models that impact on increasing interest in participating and reinforcing good data collection habits in mobile crowdsourcing.
- To identify the factors of payment-based incentives associated with the key performance metrics of interest to mobile crowdsourcing including quantity, quality, area coverage and cost.
- To develop a mobile crowdsourcing application, with payment-based incentives mechanisms.
- To design guidelines in how to create and organize payment based incentives for mobile crowdsourcing applications.

3. Scope of research

The focus of this research is on the initial exploration of the approaches to motivating user participation in mobile crowd-sensing application. We undertake a field experiment that compares several mechanisms including non-monetary and monetary approaches especially in micro-payment and referral-payment schemes. In our experiment, we develop a smart zoning application for smart cities, that allows individuals to share the areas of the cities where they feel comfort or unsafe, as a specific study scenario to explore the common principles of incentive design for mobile crowdsourcing. A set of standard metrics has been defined including quantity, quality, area coverage and cost. These key metrics are necessary conditions to design characteristics for the success of mobile crowdsourcing incentive mechanisms. We use them to evaluate the effectiveness of incentive models in data collections and report on finding from a pilot study.

Findings from the study lead to design guidelines in how to create and organize payment based incentive for mobile crowdsourcing applications. Our study enables us to answer several key questions including: 1) which incentive mechanism schemes performs well or poorly?, 2) how does the amount of payment for each mechanism impact compliance, data quality and cost?, 3) do referral-incentive strategies encourage positive or adverse behavior from participate?, 4) are the area coverage results for each incentive mechanism able to spread throughout the study's area?, 5) do users perceive payment-incentives favorably?

4. Literature Review

Mobile crowdsourcing enables the pervasive use of smartphones and other resource-rich devices to create a wide range of services, from community sensing [22] [9] [23] [12] [24] to wireless network characterization [25] and micro-task markets such as Amazon Mechanical Turk (AMT) and Micro-Workers. Although the capabilities of mobile crowd- sourcing services are increasing, the effectiveness of such systems has been claimed to critically depends on the willingness of their user's participation. For mobile crowdsourcing services to be successful, one must provide effective motivators to engage motivate a large number of individuals to participate.

Incentive mechanisms are one of the most critical factors for motivating people to contribute to a crowdsourcing effort [8] [26]. The use of effective recruitment strategies is needed as to actively engage and motivate people to contribute to crowd tasks in crowdsourcing systems. Kaufmann et al. [18] explore the workers' motivation in crowdsourcing. According to their study, motivating factors are categorized into intrinsic (e.g., enjoyment and community motivation) and extrinsic motivations (e.g., immediate payoffs, delayed payoffs, social motivation). Intrinsic motivation exists if an individual's act on the activity is driven by internal factors, e.g., acting just for fun or enjoyment. Differently, in achieving a certain desired outcome, behavior of an extrinsically motivated person is driven by external instrument; e.g., acting for money or avoiding sanctions. In addition, a recent survey on incentive techniques in participatory sensing can be found in [26]. The authors classify a taxonomy of crowdsourcing incentive mechanisms. Based on the types of stimuli that encourage user participation, this research identifies two large branches: monetary and non-monetary incentives. Monetary incentives can be either static or dynamic, whereas incentives for non-monetary mechanisms incentives include collective motives, social rewards, and intrinsic motives. Since AMT has used micro-payments as an incentive tools for task fulfillment, they are several studies that have studied the use monetary rewards to provide appropriate incentive to the participants. Mason and Watts [20] showed that higher micro-payments led to higher task completion rates on AMT but does not necessarily improve quality. Similarly, Heer and Bostock [27] used AMT to conduct a visualization study and found that larger incentives led to faster completion times but no difference in the quality of data provided across different incentive amounts. Reddy, Estrin, Hansen, and Srivastava [28] use five types of micropayments including macro, low, medium, high, and complete micropayments; their findings showed that the method used to estimate the payment affects participation level and data quality.

Micro-payments are being increasingly used in mobile crowdsourcing. The studies in incentive for mobile crowdsourcing can be classified into two groups: 1) application-independent incentive mechanism and 2) specific application scenario. For the first group, most studies target the properties such as cost minimization, utility maximization, and fairness. Koutsopoulos [29] designs an incentive mechanism based on optimal reverse auctions in order to minimize the total compensation cost but it still keeps participants motivated. Naito et al. [25] also studies micro-payment incentives in the context of participatory sensing. Their study tested multiple micro-payment amounts as well examined how game-like characteristics affect the compliance and data quality. Yang, Xue, Fang, and Tang [30] propose the models for incentive design including platform-centric and user-centric models. In the platform-centric model, the crowd takes the incentive mechanism as a Stackelberg game to maximize the utility. Another approach is an auction mechanism which derives a truthful cost declared by participants.

The second group of research on incentives for mobile-based crowdsourcing aims to develop specific application scenarios and considers incentive design as part of the application. For example, in the CrowdPark system [31], the author designed a protocol for drivers to buy and sell information about parking vacancies from and to others. The findings showed that drivers are able to receive better compensation when they follow the trading protocol and carefully configure the incentive parameters. In a similar study, Liu and Chen [32] proposed a pattern to design a crowd-based system for realizing smart parking by mobile crowdsourcing. The application is able to recruit drivers to collect information about parking occupancy and use these data to help drivers find proper parking vacancies efficiently. Their findings showed that when only useful data is rewarded, they are able to encourage participants to contribute not only their sensor data but also their intelligence in the problem-solving process. Moreover, in [33], the authors developed an application for sharing pictures of price tags by providing contributors with pricing information in nearby grocery stores.

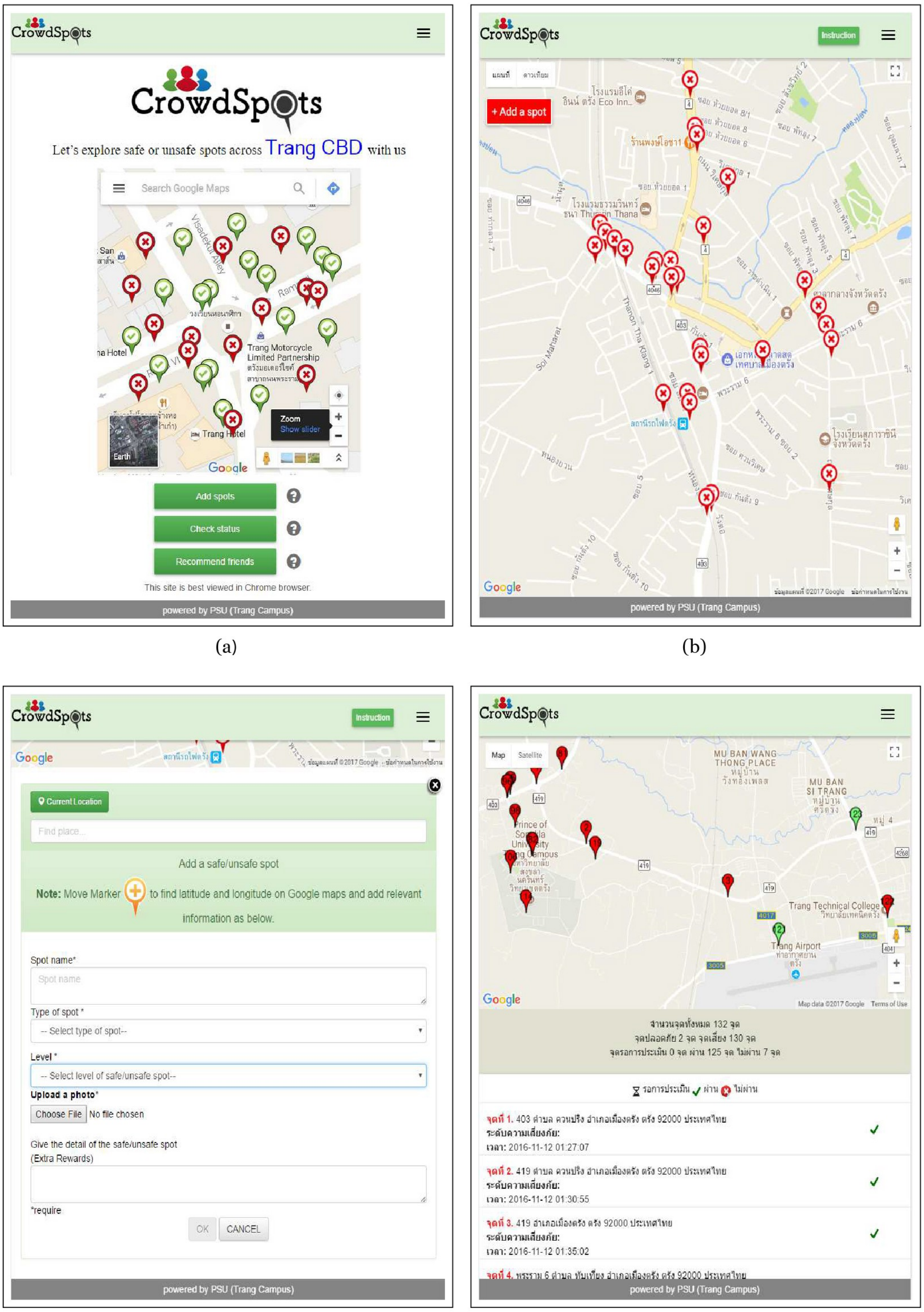
Referral or viral marketing is a highly sought-after way of advertising. This technique has received a lot of interest in the theoretical community. Kleinberg and Prabhakar [34] study a model where incentives must be provided for users to propagate a question until a node that knows the answer is reached, and Cebrian et al. [19] considered the use of recursive mechanisms in this context. Naroditskiy, Rahwan, Cebrian, and Jennings [35] provided a theoretical justification for the recursive mechanism used in the DARPA Network Challenge, and desirable properties of a referral scheme have been posed in [36]. However, these studies concentrate on theoretical issues and do not investigate or compare referral mechanisms empirically with real users. There is little existing empirical work on comparing incentives for referrals on mobile based crowdsourcing. Recently, Naroditskiy et al. [37] conducted a field experiment in the referral incentive in crowdfunding, where a field experiment was used to compare several mechanisms for incentivizing social media shares in support of a charitable cause. Under the control treatment, no extra incentive is provided. Under two of the other mechanisms, the sharers are offered a fixed number of points (1 extra point and 3 extra point) that help take the campaign further. The authors find that the 3-point mechanism is more effective than the 1-point mechanism. This is contrary to the intuition that it is not the exact value, but rather the presence of some form of incentives, which has the most effect.

Recently, crowdsourcing has been widely used for gathering public perceptions of safety or crime across in cities across the world. Hamilton, Salim, Cheng, and Choy [38] proposed a mobile crowdsourcing platform called Transafe that captures and analyzes the safety perceptions for people travelling on public transportation in Melbourne, Australia. Their framework enables the users to report crimes/misdemeanours and provide information about transportation and emergency services around where the users are located. In their work, the crowd voting mechanism has been used to aggregate people's feelings of a particular place. Safetipin [39] is another platform which used crowdsourcing to generate safety information about a city. This platform used parameters such as lighting, transportation, feeling of safety etc. to generate a safety score for a particular area. This safety information has been gathered through community volunteers and partnership with NGOs. Recent work such as [40] [41] [42] has proposed computational methods to automatically infer high level perceptual attributes from geo-referenced images of urban spaces. Such work converted the pairwise comparisons for perceived safety to ranked scores and trained a regression algorithm using generic image features to predict the ranked score for perceived safety. Such work did not focus on incentive methods to motivate people to contribute towards a crowdsourcing effort. Our study explores micro-payments for mobile sensing tasks together with a referral incentive technique. We also analyze the effects of different payment schemes on participation frequency, quality, monetary cost and coverage; also, our work, we believe, is novel in crowdsourcing the sense of safety in a part of a city in Thailand.

5. Methodology and study details

The perception of safety is important as it influences how people feel and behave towards their surroundings. Hence, we developed a mobile application that can contribute to empowering people in voicing their feelings (and so, they may feel safer) by enabling reporting of safe and unsafe spots in a part of a city in Thailand. In Thailand, road traffic accidents are the one of major causes of deaths. Thailand has a road traffic death rate of 36.2 per hundred thousand population, compared to the global rate of 17.4. Hence, it is not just crimes but also traffic that can cause one to feel unsafe at a particular spot. And the local media reports that a high percentage of commuters feel unsafe and vulnerable when they travel.

For our experiment, we have developed a mobile app that allows participants to take photos of target places and geo-tag their photos on a map called Crowdspots. In this section, we first outline key characteristics of the Crowdspots mobile crowd tasking platform. We then describe the contexts applied to the mobile crowdsourcing experiment as well as the system used in the study. Finally, deployment setup details along with metrics to evaluate incentive models are provided.



(a) (b)

(c) (d)

Figure 1. Screenshots from left to right: (a) Crowdspots main screen, (b) a map showing some areas of the city mapped by participants, (c) the submission screen, (d) the financial board with points and financial tall.

Crowdspots allows crowd workers to share information about particular areas of the city they consider as either safe or unsafe with location-based reporting tasks. Figure 1 shows the screenshots for the Crowdspots application. The architecture of Crowdspots is organized as a client-server model composing of participants/clients and a backend system/server. Clients refer to any participants working to respond to the tasks via mobile devices. Their functions are to capture and provide the user's interface. The backend-system is for data storage, processing and visualization. There are two types of users involved in this platform: 1) crowd workers/users and 2) the administrator. Workers will be asked to perform the tasks by taking geo-tagged photos of target places. The administrator views and approves photo contributions. The rewards will be finally granted by the administrator for quality tasks performed by individual workers.

5.1 Experimental design

The main purpose of this study is to investigate the effectiveness of different incentive treatments for encouraging participants to perform certain tasks. We undertake an experiment where the participants' performance of task completion was tested using four mechanisms that differ in the way they are incentivized. In completing the tasks, the participants were required to report spots they perceived as safe or unsafe in one CBD area, together with geo-tagging them on a map. The mechanisms offered a certain reward for spots reported. The reward was expressed in terms of incentivized payment and differs across the mechanisms as follows:

(1) **Fixed-price payment** – Participants are given 5 baht (20 Australian cents) for every single task they completed. Extra rewards worth 2 baht are offered only in case they add the caption to each photo. (1 AUD = 25 Baht);

(2) **Low-price referral payment** – Participants are offered the same payment rate as those in the fixed-price payment group. Extra payment of 5 baht will also be awarded to them for successfully referring each person to complete the task;

(3) **High-price referral payment** – Apart from being given 5 baht for each task, the participants will receive an extra reward of 75 and 200 baht for successfully referring 10 and 25 people respectively to complete the task; and

(4) **Non-payment** – Non-monetary incentives are provided for participants in this group. Their participation is volunteer-based and thus taken as a base case treatment.

Based on the incentive mechanisms mentioned above, participants were divided into two main groups: an experimental group and a control group. The participants exposed to the first three monetary incentives were put in the experimental groups, whereas the ones with non-payment are the control group.

The Crowdspots application was deployed by participants for a week, starting from the middle of the week (Wednesday). The participants were asked to tag geo-locations and capture images of places. Prior to starting work, the participants were informed about the purpose and length of the study, trained on how to tag and collect images, and informed only about the specific incentive they belonged to. They were also asserted that only clear (not blurry or too dark) images of place contents that were considered as valid and will consequently be rewarded for. Collecting data on the same place by the same user was not allowed. Under referral mechanisms, the participants who referred tasks to others would receive extra rewards only when their referrals signed up to the application, together with generating a successful given task.

Importantly, any referrals would receive the same incentive as the original groups of participants.

5.2 Participant recruitment

The strategies we used to recruit participants in this study were guided by the study purpose and design. As the study aims at comparing four treatments that differ in the incentivized mechanisms, both paper and electronic versions of advertising flyers were distributed throughout one university to approach participants. There were two phases of task-related advertisement, non-monetary and monetary. In the non-monetary tasks phase, individuals were made clear that no monetary rewards were given for working on tasks so that they could to determine if they were willing to assist with recruitment efforts. People of the other phase were told about being paid after completing tasks. Upon completion of the recruitment process in the monetary task phase, the participants were randomly assigned to each of the three treatments (the experimental groups). The participants were affirmed that their decision to participate or not to participate would not affect their relationship with the researchers and the university in any way.

In this recruitment process, we decided to set the number of participants to be equal for each treatment. This decision not only made fair and reliable comparisons of effectiveness of the treatments but also enabled us to manage a budget more effectively. Ten students who responded to the call for participation in each treatment were then recruited for initial work. Since referral mechanisms allow invitations of other people, an additional 74 participants were recruited. There was thus a total of 114 participants used for quantitative data analysis.

5.3 Measurement Parameters

There four key performance metrics of interest to mobile crowdsourcing: quantity, quality, area coverage and cost.

- **Quantity** – It represents the number of tasks that are completed by participants. It can be compared over different time intervals during the data collection period (for instance, submission per hour or day).
- **Quality** – The quality is measured by the participants' abilities in capturing the photos of the target places. In other words, the completeness of tasks captured is indicative of the quality - whether the photos captured are totally incomplete or partly complete (e.g., a mismatch between a place captured and its photo or the amount of image noise). In this regard, the percentage of invalid photos of the places (e.g., whether they are blurred or too dark to see) are calculated, together with calculation of percentage of optional annotations provided as captions on the photos. Three people were invited to evaluate the quality; two are people who are familiar with the areas investigated due to their daily commuting and the other is a government official whose work is related to provincial transportation and security.
- **Area coverage** – This refers to the spatial and temporal extent associated with samples provided by participants.
- **Monetary cost** – This cost refers to the total earnings of all users in three different groups of participants using different incentive approaches, i.e. the estimated expenses the researcher has to pay these participants for the responses (i.e., tasks) they provide.

5.4 Statistical Analyses

Both descriptive and inferential statistical tests were carried out in this study. First, the simple statistical test (i.e. the means, modes, frequencies and percentages) was intended to describe participants in terms of the number of tasks completed and the number of invalid data created in each of the approaches. Second, the inferential statistical test was used to examine whether there were any significant differences in the four key performance metrics (as mentioned in the section above) across the four incentives to mobile crowdsourcing. To compare the differences in medians among four student groups, we used Kruskal-Wallis analyses of ranks. This test is considered as appropriate to the current study since it can determine the significance of difference among three groups even when the distribution of the data is not normal. All tests of significance used two-tailed p values. Specific group differences were examined by using post-hoc non-parametric group comparison method. Throughout the study, the alpha level for tests of significance was set at $\alpha < 0.05$.

6. Quantitative results and analysis

In this section, we analyzed the results from our data collection. For our experiment, quantity was defined by the total number of photos and tag geo-coordinate on the map submitted by the participants for a week. Quality was measured by analyzing the percentage of correctness of the photos submitted, together with calculations on percentage of optional annotations provided with the captions on the photos. Cover- age was computed by taking into account the number of spatial blocks and temporal periods of the participants. Frequencies of data across the four groups were compared using chi-square analysis. Since the behaviors within each group did not follow a normal distribution, the non-parametric Kruskal-Wallis test was carried out to test significant differences between the groups, using two-tailed p values. Specific group differences were finally examined by post-hoc non-parametric group comparison methods. Bonferroni correction was used because it is highly flexible, simple to compute and can control for inflating Type I errors (i.e., the bias caused by multiple comparisons).

Table 1. The total number of participants, task submitted, expenses, correctness and photo description by each group

Incentive Method	Partici-pants	Tasks submitted	Total expenses	Correct-ness	Photo description
Fixed-price	10	132	875	125	130
Low-price referral	52	175	1,260	164	171
High-price referral	45	146	1,059	137	142
non-payment	7	47	-	38	35

Overall, Crowdspots proved very successful in allowing us to map and monitor safe or unsafe areas around Trang CBD. Over a week, the participants made 500 recordings in total and added safe/unsafe spot areas to the database. As illustrated in Figure 1b, this resulted in detailed mapping of safe and unsafe spot areas in the Trang city center. And the participants were between 17 and 25 years old. Table 1 shows the total number of participants using each of the incentive mechanisms, together with the total number of outputs submitted by the participants, expenses, correctness and optional captions on the photos. To analyze the characteristics of different incentive plans, the results are described according to the key performance metrics of interest to mobile crowdsourcing in the following section.

6.1 Participation

The number of submissions made under each of the incentive type is shown in Table 1. It was clearly seen that the low-price referral method achieved the highest number of participants and task submission whereas the least successful one was the non- monetary model. The finding showed that the highest number of output tasks (175 tasks submitted) is derived through the use of low-price referral approach. Meanwhile, the number of participation output in the high-referral and fixed payment are 146 and 132, respectively. Remarkably, the non-payment approach is the least popular; just only 47 tasks were completed by participants. Although low-price referral treatment had the highest output, the individual user participation rates varied greatly.

Due to a lack of a normal distribution of the data, the non-parametric Kruskal-Wallis Test was carried out to test the differences in incentives between the groups. The result showed a statistically significant difference in the number of data collection output among the different incentive treatments, $\chi^2= 20.41$, $p = 0.00$, with a mean rank score of 67.80 for non-payment, 107.15 for fixed-price, 54.80 for low-price referral and 58.44 for high-price referral method. We then conducted the post-hoc Kruskal-Wallis Tests, with results from Bonferroni correction displayed in Table 2.

Table 2. The post-hoc results of participants' submissions with Bonferroni correction

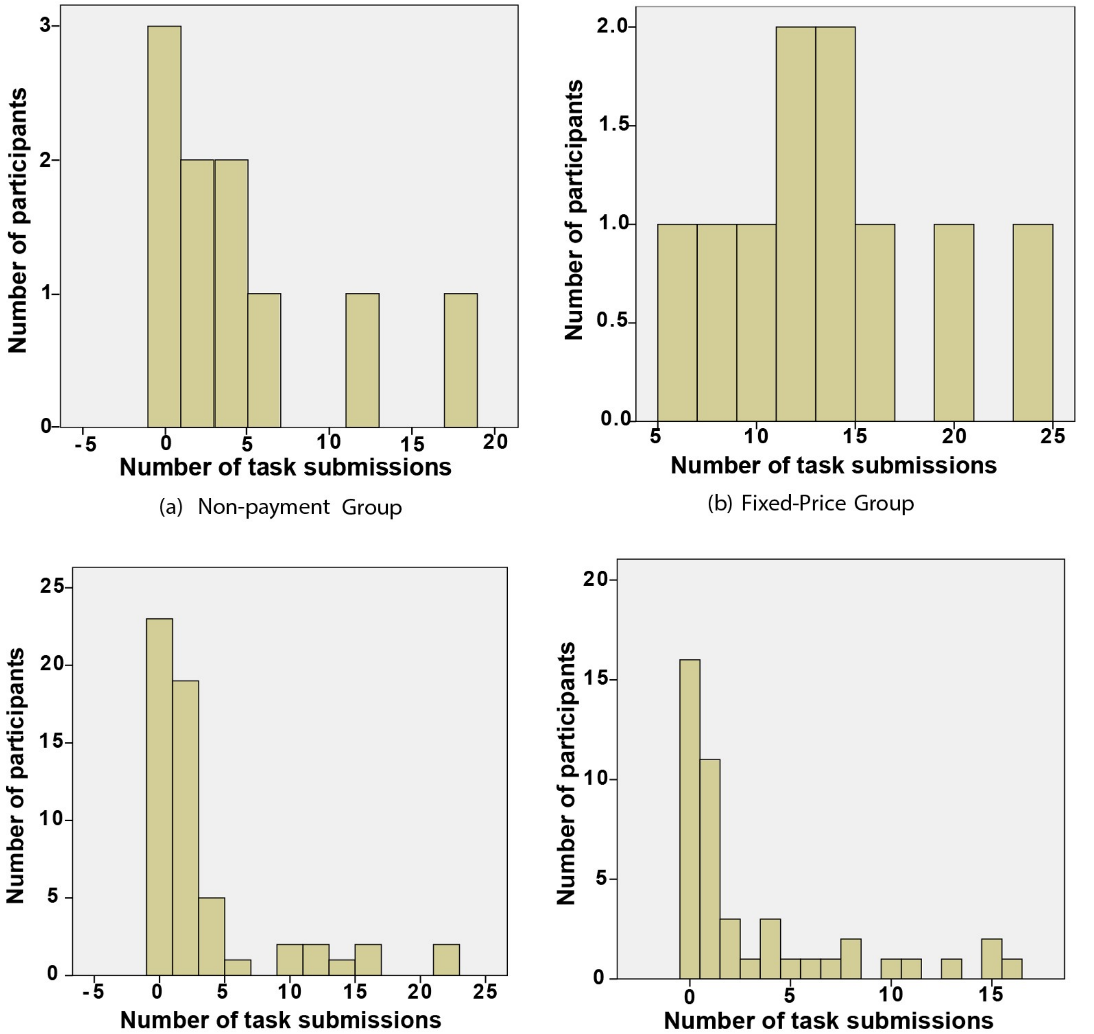
Sample1-Sample2	Test Statistic	Std. Error	Std.Test Statistic	Sig.	Adj.Sig.
low referral - high referral	-3.646	6.869	-.531	.596	1.00
low referral - non payment	13.002	11.809	1.101	.271	1.00
low referral - fixed price	52.352	11.809	4.433	.000	.000
high referral - non payment	9.356	12.042	.777	.437	1.00
high referral - fixed price	48.706	12.042	4.045	.000	.000
non payment - fixed price	-39.350	15.404	-2.554	.011	.064

When we conducted post-hoc analysis to test pairwise multiple comparisons. Findings suggested that the location tagging and photos added by a participant from the fixed-price group were significantly greater than those in the low-price referral (p = 0.00) and high-price referral (p = 0.00) groups. Consider the average of task submissions per person in fixed-price group that was 13.2 whereas those in low-price and high-price approach were only 3.07 and 3.24 respectively (see in Table 3). Moreover, findings showed that there was no significant difference in performance of the participants of the fixed-price and non-payment groups. However, the higher number of task submissions in the fixed-price group outperformed the non-payment group. It should be also noted that the mean in the fixed-price group (13.2) is greater than that of non-payment group (4.7) and the median of the fixed-price group (12.5) also is higher than of non-payment group (3.0). These values are shown in Table 3.

Table 3. Overall data collection participation submissions

Incentive Methods	Total	Mean	Median	Min	Max
Fixed-price	132	13.2	12.5	6	23
Low-price referral	175	3.07	1	0	21
High-price referral	146	3.24	1	0	16
Non-payment	47	4.7	3	0	18

Although the number of outputs of participants of both low and high price referral incentive types was much greater than that of the non-monetary group (see in Table 3), the result showed that there was no statistically significant difference across the non-payment, low-price referral and high-price referral groups. The low-price referral group received the highest number of participant responses, but this group had the smallest score (3.07) as compared with other counterparts. Similarly, the mean of high-referral (3.24) was found to be slightly different from those of the low-price referral group. The report also showed the medians of both groups (low and high price referral = 1) was less than the median of the non-monetary group (3).



(a) Non-payment Group (b) Fixed-Price Group (c) Low-Price Referral Group (d) High-Price Referral Group

Figure 2. The frequency distribution of the number of participant submissions by each group

To further investigate the above issues, we decided to compare the data distribution of individuals in each group. The frequency distribution of all participant submissions was then plotted (see Figure 2). Results showed that the frequencies of low and high price referral groups were not normally distributed, and they were mainly distributed with value near 1. When looking into details of the participant data, we found that task submissions by 1 response had been mostly done by the people who joined via a referral. Here, it is interesting to note that there are two participant groups: 1) an invited group and 2) a referral group. The invited group refers to original participants who were recruited into the study and randomly assigned into each treatment, whereas the participants who obtained tasks through the direction of the invited participants fell into the referral group (only low and high price referral groups).

Table 4 shows the percentage of the number of participants and data collection output by each type of participants. Participants with low and high price referral types were offered the extra reward in the case that they could invite other people to complete the tasks. The results showed that the percentage of the number of referral participants (80.8% and 79.5%) was much greater than that of the invited participants (19.2% and 20.5%) in low and high price referral groups. In contrast, the number of submissions by referral participants (24% and 30.1%) was less than the percentage done by invited participants (76% and 69.9%) for low and high referral groups, respectively. Overall, both of the low and high price referral incentive approaches appeared to motivate the higher invited participants, but it demotivated the majority of the referral participants. This issue was further investigated and analyzed using data from semi-structured interviews (see the detail in Section 5).

Table 4. The percentage of the number of participants and data collection output by each type of participants.

Incentive Methods	Num. of invited participants (%)	Num. of referral participants (%)	Num. of submission by invited participants (%)	Num. of submission by referral participants (%)
Low-price referral	19.2	80.8	76	24
High-price referral	20.5	79.5	69.9	30.1

6.2 Quality

The quality of data derived from using different incentive models was analyzed. Results from the Kruskal-Wallis Test revealed that there was a significant effect of correctness of task submissions across the different incentive mechanisms, $\chi^2 = 20.75$, $p = 0.0$, with the mean rank scores of 66.80, 107.55, 54.80, and 58.58 for groups of non-monetary, fixed-price, low-referral and high-referral, respectively. We then conducted the post-hoc Kruskal-Wallis Tests, with Bonferroni correction. The results were displayed in Table 5.

Table 5. The post-hoc results of output quality with Bonferroni correction

Sample1-Sample2	Test Statistic	Std. Error	Std.Test Statistic	Sig.	Adj. Sig.
low referral - high referral	-3.780	6.843	-.552	.581	1.00
low referral - non payment	12.002	11.764	1.020	.308	1.00
low referral - fixed price	52.752	11.764	4.484	.000	.000
high referral - non payment	8.222	11.996	.685	.493	1.00
high referral - fixed price	48.972	11.996	4.082	.000	.000
non payment - fixed price	-40.750	15.345	-2.656	.008	.048

The finding showed the correctness of the fixed-price group was significantly greater than in those of the non-payment, low-price referral and high-price referral groups. Nevertheless, there was no significant difference in the correctness among non-monetary, low-price referral and high-price referral groups. We also explored the validity of task submissions; that is, it was to check whether the photos captured were totally incomplete or partly complete; e.g., a mismatch between a place captured and its photo (invalid coordinates) or the amount of image noise (blurred or too dark to see, invalid photos). In this regard, the percentage of invalid photos of the places was calculated. Based on the number of output errors, the percentages of them were displayed in Table 6. It was clearly shown that the non-monetary method had the largest percentage of invalid output (19.2%) whereas the fixed-price method received the least of errors (5.3%). In addition, the errors caused by the invalid photo were found to be more common than the errors by invalid coordinate in all four groups. Features of the in- valid photos include poor quality of the photos taken (too dark or too bright) and imprecision of unsafe/safe spots focused on.

Table 6. The percentage of overall error, invalid photos and invalid coordinates by each group

Incentive Methods	Overall error (%)	Invalid photo (%)	Invalid coordinates (%)
Fixed-price	5.3	71.43	28.57
Low-price referral	6.3	63.64	36.36
High-price referral	6.2	66.67	33.33
Non-payment	19.2	75.00	25.00

The participants can get extra rewards by adding a caption to each of the photos. The percentages of photo description are presented in Table 7. The results showed that participants mostly provided the captions of the images. Remarkably, the smallest percentage fell in the non-payment group (74.47%), whereas the percentages of the three counterparts were found to be higher 90%.

Table 7. The percentages of photo description by each group

Incentive Methods	Num. of optional description (%)
Fixed-price	94.70
Low-price referral	91.43
High-price referral	93.84
Non-payment	74.47

6.3 Monetary cost

The cost/expense used in this study refers to the total amount of money paid to the participants for the completion of crowd tasks performed. The total expenditures for each crowdsourced experiment have been shown in Table 1. The result showed that the highest cost fell in the low-price referral treatment (1,260 baht), followed by the high- price referral group (1,059 baht) and the fixed-price group (875 baht). When using a Kruskal-Wallis Test to find association of rewards among experimental incentive techniques, we found that there was a statistically significant difference in the rewards (participants' income) offered to the participants using different incentive treatments, χ^2= 29.73, p = 0.00, with a mean rank reward score of 26.50 for non-payment, 107.60 for fixed-price, 58.39 for low-referral and 62.97 for high-referral methods. We then conducted the post-hoc Kruskal-Wallis Tests, with results from Bonferroni correction displayed in Table 8.

Table 8. The post-hoc results of monetary cost with Bonferroni correction

Sample1-Sample2	Test Statistic	Std. Error	Std.Test Statistic	Sig.	Adj. Sig.
non payment - low referral	-31.895	11.619	-2.745	.006	0.36
non payment - high referral	-36.467	11.848	-3.078	.002	0.13
non payment - fixed price	-81.100	15.156	-5.351	.000	.000
low referral - high referral	-4.572	6.758	-.677	.499	1.00
low referral - fixed price	49.205	11.619	4.235	.000	.000
high referral - fixed price	44.633	11.848	3.767	.000	.001

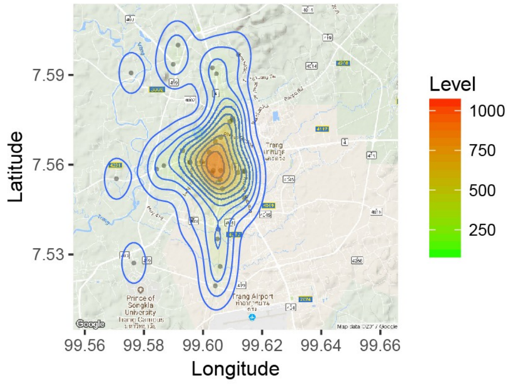
Results from the post hoc comparison revealed significant differences in five pairs of incentives: 1) non-payment and fixed-price group 2) non-payment and low-price referral 3) non-payment and high-price referral 4) low-price referral and fixed-price group and 5) high-price referral and fixed-price group, indicating that different incentives impact upon how different the earnings would be. It should also be noted that the finding shows the highest earnings fallen in the fixed price payment, probably suggesting that when earnings or rewards are under the participants' own control (they could make their own decisions on how much work to be completed, as in fixed-price group), rather than being dependent on others (as in two referral groups), they are likely to be more engaged or more active in working on the tasks. No significant differences in earnings were found between low-price referral and high-price referral.

In addition, we analyzed the correlation between earnings/rewards and correctness of the responses to investigate the relationship between them. We found a significant correlation between the earnings/rewards and quality of takes they submitted ($p < 0.05$). This means earnings/rewards are ones of effective incentives - the more earnings/rewards the participants receive, the higher the quality of their tasks is expected to be.

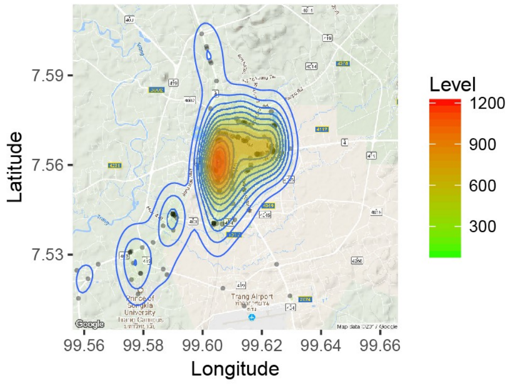
6.4 Coverage

In the study, the design that the participants were required to geo-tag photos for a week in Trang CBD allowing us to see various areas, either safe or unsafe, on a map. To analyze the coverage provided by participants, we plot the density of out- puts/contributions on a heat map. The heat map for each incentive type is presented in Figure 3. In the heat map, we can see spots tagged by the participants. The density of those spots was identified by different colors 'red' for the highest density of tags and 'green' for the lowest density. The heat map indicates that low-price referral had the most coverage, followed by high-price referral and fixed-price incentive types, whereas the non-monetary group yielded the least coverage.

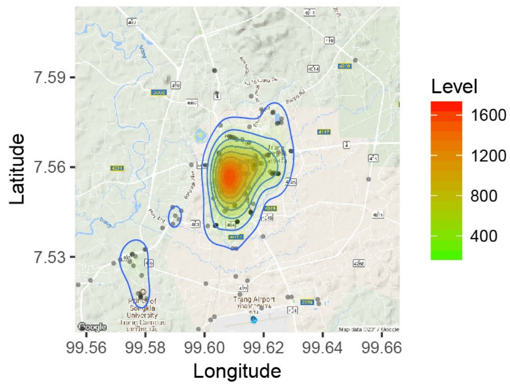
Furthermore, we investigated the different periods tasks were being posted in a week by the participants from across four different incentives. As Figure 4 presents, there was no obvious difference in time periods the participants decided to post their tasks; that is, posting over the weekends seemed to be their most preferable time and the postings reduced by the end of the week.



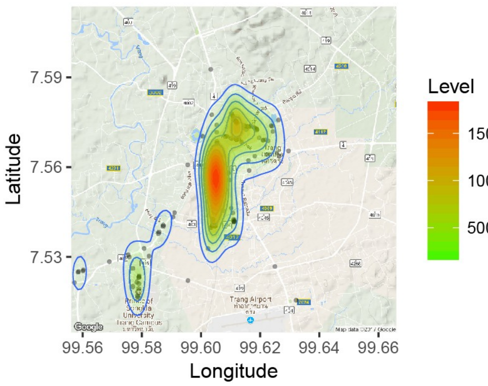
(a) Non-payment Group



(b) Fixed-Price Group

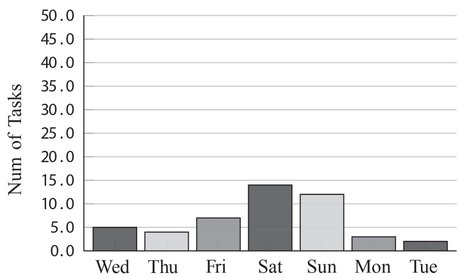


(c) Low-Price Referral Group

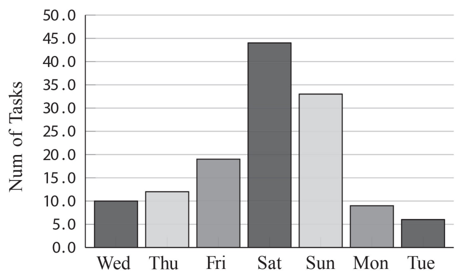


(d) High-Price Referral Group

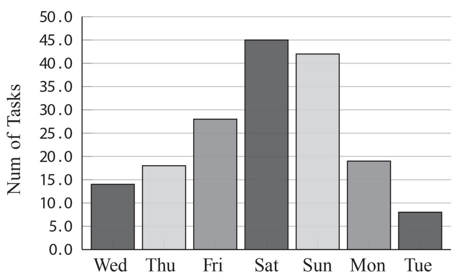
Figure 3. The heat map of each treatment



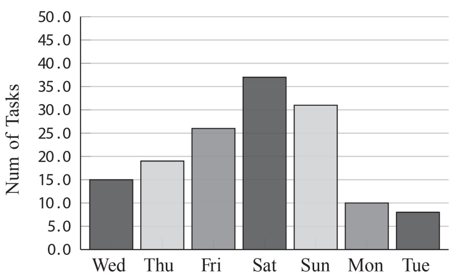
(a) Non-payment Group



(b) Fixed-Price Group



(c) Low-Price Referral Group



(d) High-Price Referral Group

Figure 4. Daily task submissions in a week by the participants of across four different incentives

7. Qualitative results and analysis

This section addresses participants' first-hand experience in using the application in this project and factors that motivate them to do tasks. The results presented in this section were derived from semi-structured interviews with 12 participants, three from each of the four group.

The interviews were audio-recorded, transcribed verbatim and translated from Thai language to English. We then undertook a thematic analysis [43]. The key themes that emerged from the analysis are discussed below. The interview questions covered the participants' perception when they completed tasks using the application, i.e., their impression of (1) the application generally, (2) the usage of location information and images for task assignments, (3) satisfaction with incentives provided, (4) time and work management, and (5) other constraining factors.

7.1 Usability of the app

Most of the interviewed participants felt that the app was intuitive and easy-to-use. For example: "I have no difficulties in the use, only three steps were needed to report the location and post the photo." However, some participants seemed to suffer when they tried to upload photos because their photos were too big and took a long time for them to upload. Overall, it is unlikely that basic usability issues impacted on the results of our study.

7.2 Performance-related financial incentive

As shown in the previous section, all financial groups including fixed-price, low-price referral and high-price referral gathered a significantly greater quantity of data sub- missions, confirming that the financial incentive could motivate users far more than non-payment motivation did. However, this motivating effect came with a cost for the task provider, as shown in the findings. Interviewed participants in all financial groups were satisfied with the hiring rate, and they reported on their 100% willingness to do more. In contrast, there was only one non-payment participant who performed tasks without expecting payment who was willing to continue.

For incentive programs, all interviewed participants were satisfied with both low and high referral approaches that made use of through friend connections or viral marketing. Some of their comments that reflect this satisfaction are: "Encouraging friends to work on tasks is my way to earn more money", "I've not found difficulties in inviting friends to join this job", and "The more friends I can invite, the more money I can earn". It appeared that most participants spread the word via their social networks,
e.g. Facebook, Twitter or Instagram. They added that social networks made sharing information very easy and fast. In their opinion, posting tasks through social networks helped them reach a large audience with no need for providing detailed explanations. In addition, messenger or chat platforms were their preferred methods in distributing their messages towards targeted friends or people who may share similar interests.

7.3 Socio-cultural drives

The interview data revealed that all students in a non-payment group in particular reported on their willingness to participate in the task project. Their reasons for this participation appeared to arise from socio-cultural factors. The students' perceptions viewing the researchers as their former lecturer impacted upon their decisions to participate, as supported by their comments: "I used to be your student in the previous courses," (Student A) and “I’m feeling like it’s a good opportunity for me to work with you and learn how to work from you," for instance. This finding can be partly explained through a socio-cultural lens. Thai traditional beliefs view teachers as the givers of knowledge and the second parents of students. The students in this study then regarded their participation as a way to express "feelings of being grateful" to their teachers: "You are my lecturer and would like to help you (to do this project)."

Another factor that has influenced the participants to do tasks is a sense of collectivism, the idea that the individual’s life belongs to a group. The interview data revealed that the majority of student participants who joined the project via referral approach was friends of friends. Following are some of the examples that illustrated this phenomenon: "I decided to join this project because my friend requested me to do so", "I just helped my friend. She posted on Facebook a request for this help.” This finding suggests that a sense of harmony and a high level of group orientation have a positive impact upon initial willingness to perform tasks. However, it seemed that the participants in referral groups failed to work actively on this project as only a few spots were tagged by them. This lack of active engagement was supported by the statement: "I worked on this task just because of my friend’s request." This finding supports quantitative results; that is, the majority who joined the project through a word-of-mouth tended to submit only few outputs. A possible explanation for these results may be the lack of internal motives; that is, the participants felt they were engaging in tasks because they were pressured by some other external factors (i.e., friends’ request), rather than choosing to do so by themselves. As such, the ability to devote extra time to complete tasks is restricted, as evidenced in this study. There could also be other motivational factors, such as building the map as a reference to help improve safety in the area, but was not explored further in this study.

7.4 Working strategies

The interview data helps to explain results from the quantitative analysis that the least outputs were submitted by non-monetary participants. The participants in this group admitted that they would work on tasks only when "time" and "convenience" permitted: "I had no class over the weekends and it’s my free time" or "I was about to visiting the places for my personal purposes" (e.g., dining and doing errands). In short, they had no goal-oriented intention to do the tasks, which certainly impact upon the number of tasks performed. Differently from the other three groups who were payment-related, they set plans for work and tried to make themselves more disciplined in achieving the tasks, as evidenced in some of their instances: "I planned to work on tasks every day, two hours a day at least", "My plan was to collect at least five points a day", and "I tried not to give up my plan; I did it every day after class".

Based on the results from the interviews, it should be noted that in all incentive mechanisms, there are similarities in terms of data collection behavior. The participants mostly reported on spending their free time, especially during weekend doing the tasks. By making a list of spots to investigate, many of them could not only maximize their time but also save cost: for example, "I set a plan for places, safe or unsafe, to visit in particular so that I won’t waste much money on fuel expenses", and "I started working on things most familiar to me. I mean the places in my area. Rather than keep riding, I knew exact destinations. This helped save my time".

A similarity in working behavior was also mentioned regarding their data submission or posting. The participants started by taking photos of places investigated and recorded relevant data on either on mobile phones or notepaper. By the end of each day of data collecting, they would upload data (photos, captions, and relevant details) into the system using Wi-Fi available in their accommodations/university. These stu- dents tried to avoid using 3G/4G in data uploading in order to save costs: for example, "I uploaded data every day at night through Wi-Fi of the university. This saved my money" and "I would use 3G (in submitting tasks) only when Wi-Fi at home was very slow or didn't work".

7.5 Constraints

Data from interviews enabled insight into constraints participants perceived while collecting data. 70% of the participants requested extending the period for collecting data. Some of their typical reasons for this request are: "If I was given more time, like 2 weeks longer, I would be able to gather more data. Some days my time was really tight being busy with assignments and studies", "If possible, I want 15 days more for this job because the friends I had invited weren't available during that rather short period" and "I'd say one week has never been enough for me to get more data, especially when I had quizzes to prepare for".

Apart from that, there were external factors that imposed constraints on the participants' ability to collect data. The majority agreed that the end of the year in southern Thailand was not the time suitable for data collection, as shown in the statement, "In this rainy season, it's hard for me to go outside by motorbike to collect data". Additionally, many participants expressed their personal fear of using mobile phones when it was starting to rain. The quality of work affected by the weather conditions was also part of their concern, as in "I think even taking photos during cloudy days wasn't a good idea".

8. Discussion and Conclusion

In this paper, we investigated the use of incentive mechanisms based on monetary and non-monetary approaches. We have assessed the impact of different motivating factors and designed strategies related to participants' performance of collecting and sharing data in a mobile safety crowdsourcing application. The study indicates the importance of how to design task-completed mechanisms in a way that would most engage people who may differ in their motivations.

The current study indicates that money is one crucial incentive in this task-based project, even if payments are relatively small. The payment-related incentives not only encourage people to actively participate in the project but also incentivized their good data collection behavior and task quality, as found in this study. The participants with money incentives were found to set up the "goals" to achieve in terms of the amount of money to earn in each day. However, a reduction of the participants' long-term intrinsic motivation that is evidenced should also be noted.

Among payment-related mechanisms, a fixed-price financial mechanism seems to be most appropriate for short period data collection with the aim of achieving data quality. Through referral incentives with proper designs, participant coverage tends to be largely extended, either spatially or temporally. It is also interesting to note that the low-price referral method became more motivating than the high-price referral one. One possible explanation for this may be participants' perceptions of task difficulties and possibilities to reach rewards. The participants in a high-price referral group may find it hard to complete more complicated tasks despite high payment offered to them. This perceived hard to reach rewards thus fail to encourage them to make sufficient effort to work on the tasks though their potential exists.

The non-monetary incentive mechanism seems to be motivating if it is compatible with socio-cultural values people are holding. The case of student participants in this study can be an example. These Thai students grew up in a collectivistic culture and had the characteristic of feeling indebted to the researcher who had been their former lecturer. They thus responded to a call for this study with no expectation of money in return. In this regard, it can be said that culture is a possible factor that determines incentive system success. This result could contribute to the strategic formulation of developing incentives mechanisms in other countries that have similar socio-cultural environments.

Future research recommendations include an experimental design conducted with a larger group of participants for the generalization of findings. It is also interesting to see whether individuals' demographic composition affect their decisions made on participating in tasks of different incentives and in what way incentives mechanisms impact upon their performance on tasks completion.

References

[1] Yuen MC, Chen LJ, King I. A Survey of Human Computation Systems. In: Computational Science and Engineering, 2009. CSE '09. International Conference on; Vol. 4; 2009. p. 723– 728. Available from: 10.1109/CSE.2009.395.

[2] Yuen MC, King I, Leung KS. A Survey of Crowdsourcing Systems. In: Privacy, Security, Risk and Trust (PASSAT) and 2011 IEEE Third Inernational Conference on Social Com- puting (SocialCom), 2011 IEEE Third International Conference on; 2011. p. 766–773. Available from: 10.1109/PASSAT/SocialCom.2011.203.

[3] Quinn AJ, Bederson BB. Human Computation: A Survey and Taxonomy of a Growing Field. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Sys- tems; New York, NY, USA. ACM; 2011. p. 1403–1412. Available from: 10.1145/1978942. 1979148.

[4] Morschheuser B, Hamari J, Koivisto J. Gamification in crowdsourcing: a review. In: 2016 49th Hawaii International Conference on System Sciences (HICSS). IEEE; 2016. p. 4375– 4384.

[5] Goodchild MF, Glennon JA. Crowdsourcing geographic information for disaster response: a research frontier. International Journal of Digital Earth. 2010;3(3):231–241.

[6] Oomen J, Aroyo L. Crowdsourcing in the cultural heritage domain: opportunities and challenges. In: Proceedings of the 5th International Conference on Communities and Tech- nologies. ACM; 2011. p. 138–149.

[7] Swan M. Crowdsourced health research studies: an important emerging complement to clinical trials in the public health research ecosystem. Journal of medical Internet research. 2012;14(2):e46.

[8] Chatzimilioudis G, Konstantinidis A, Laoudias C, et al. Crowdsourcing with Smartphones. IEEE Internet Computing. 2012;16(5):36–44. Available from: 10.1109/MIC.2012.70.

[9] Mata F, xe, lix, et al. A Mobile Information System Based on Crowd-Sensed and Official Crime Data for Finding Safe Routes: A Case Study of Mexico City. Mobile Information Systems. 2016;2016:11. Available from:

10.1155/2016/8068209.

[10] Franke T, Lukowicz P, Blanke U. Smart crowds in smart cities: real life, city scale de- ployments of a smartphone based participatory crowd management platform. Journal of Internet Services and Applications. 2015;6(1):1–19. Available from: 10.1186/s13174-015- 0040-6.

[11] Guo B, Chen C, Zhang D, et al. Mobile crowd sensing and computing: when participa- tory sensing meets participatory social media. IEEE Communications Magazine. 2016; 54(2):131–137. Available from: 10.1109/MCOM.2016.7402272.

[12] Wang X, Zheng X, Zhang Q, et al. Crowdsourcing in ITS: The State of the Work and the Networking. IEEE Transactions on Intelligent Transportation Systems. 2016;17(6):1596– 1605. Available from: 10.1109/TITS.2015.2513086.

[13] Zheng X, Chen W, Wang P, et al. Big Data for Social Transportation. IEEE Transactions on Intelligent Transportation Systems. 2016;17(3):620–630. Available from: 10.1109/TITS. 2015.2480157.

[14] Vergara-Laurens IJ, Labrador MA. Preserving privacy while reducing power consump- tion and information loss in LBS and participatory sensing applications. In: 2011 IEEE GLOBECOM Workshops (GC Wkshps); 2013. p. 1247–1252. Available from: 10.1109/GLOCOMW.2011.6162381.

[15] Vergara-Laurens IJ, Mendez-Chaves D, Labrador MA. On the Interactions between Privacy-Preserving, Incentive, and Inference Mechanisms in Participatory Sensing Systems . 2013. Available from: 10.1007/978-3-642-38631-2_47.

[16] Yerva SR, Jeung H, Aberer K. Cloud based social and sensor data fusion. In: Information Fusion (FUSION), 2012 15th International Conference on; 2012. p. 2494–2501.

[17] Doan A, Ramakrishnan R, Halevy AY. Crowdsourcing Systems on the World-Wide Web. Commun ACM. 2011 April;54(4):86–96. Available from: 10.1145/1924421.1924442.

[18] Kaufmann N, Schulze T, Veit D. More than fun and money. Worker Motivation in Crowdsourcing-A Study on Mechanical Turk. In: Americas Conference on Information Systems (AMCIS), 4-7 August 2011. Detroit, Michigan; 2011.

[19] Cebrian M, Coviello L, Vattani A, et al. Finding Red Balloons with Split Contracts: Robustness to Individuals' Selfishness. In: Proceedings of the Forty-fourth Annual ACM Symposium on Theory of Computing; New York, NY, USA. ACM; 2012. p. 775–788. Available from: 10.1145/2213977.2214047.

[20] Mason W, Watts DJ. Financial Incentives and the "Performance of Crowds. In: Proceed- ings of the ACM SIGKDD Workshop on Human Computation; New York, NY, USA. ACM; 2009. p. 77–85. Available from: 10.1145/1600150.1600175.

[21] Leesa-Nguansuk S. Thailand makes top 10 in social media use. 2018 March. Available from: https://www.bangkokpost.com/tech/local-news/1420086/thailand-makes-top-10- in-social-media-use.

[22] Guo H, Dai G, Fan J, et al. A Mobile Sensing System for Urban Monitoring with Adaptive Resolution. Journal of Sensors. 2016;2016:15. Available from: 10.1155/2016/7901245.

[23] Murphy E, King EA. Smartphone-based noise mapping: Integrating sound level meter app data into the strategic noise mapping process. Science of The Total Environment. 2016;562:852–859. Available from: http://dx.doi.org/10.1016/j.scitotenv.2016.04.076.

[24] Mata F, xe, lix, et al. A Mobile Information System Based on Crowd-Sensed and Official Crime Data for Finding Safe Routes: A Case Study of Mexico City. Mobile Information Systems. 2016;2016:11. Available from: 10.1155/2016/8068209.

[25] Naito K, Tani S, Takai D. Implementation of Mobile Sensing Platform with a Tree Based Sensor Network . 2016.

[26] Jaimes LG, Vergara-Laurens IJ, Raij A. A Survey of Incentive Techniques for Mobile Crowd Sensing. IEEE Internet of Things Journal. 2015;2(5):370–380. Available from: 10. 1109/JIOT.2015.2409151.

[27] Heer J, Bostock M. Crowdsourcing Graphical Perception: Using Mechanical Turk to As- sess Visualization Design. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems; New York, NY, USA. ACM; 2010. p. 203–212. Available from: 10.1145/1753326.1753357.

[28] Reddy S, Estrin D, Hansen M, et al. Examining Micro-payments for

Participatory Sens- ing Data Collections. In: Proceedings of the 12th ACM International Conference on Ubiquitous Computing; New York, NY, USA. ACM; 2010. p. 33–36. Available from: 10.1145/1864349.1864355.

[29] Koutsopoulos I. Optimal incentive-driven design of participatory sensing systems. In: IN- FOCOM, 2013 Proceedings IEEE; 2013. p. 1402–1410. Available from: 10.1109/INFCOM. 2013.6566934.

[30] Yang D, Xue G, Fang X, et al. Crowdsourcing to Smartphones: Incentive Mechanism Design for Mobile Phone Sensing. In: Proceedings of the 18th Annual International Con- ference on Mobile Computing and Networking; New York, NY, USA. ACM; 2012. p. 173–184. Available from: 10.1145/2348543.2348567.

[31] Yan T, Hoh B, Ganesan D, et al. CrowdPark: A crowdsourcing-based parking reservation system for mobile phones. University of Massachusetts at Amherst Tech Report. 2011;.

[32] Liu N, Chen X. Contribution-Based Incentive Design for Mobile Crowdsourcing. In: Man- agement of e-Commerce and e-Government (ICMeCG), 2014 International Conference on; 2014. p. 151–155. Available from: 10.1109/ICMeCG.2014.39.

[33] Deng L, Cox LP. LiveCompare: Grocery Bargain Hunting Through Participatory Sensing. In: Proceedings of the 10th Workshop on Mobile Computing Systems and Applications; New York, NY, USA. ACM; 2009. p. 4:1–4:6. Available from: 10.1145/1514411.1514415.

[34] Kleinberg J, Prabhakar R. Query incentive networks. In: 46th Annual IEEE Symposium on Foundations of Computer Science (FOCS'05); 2005. p. 132–141. Available from: 10. 1109/SFCS.2005.63.

[35] Naroditskiy V, Rahwan I, Cebrian M, et al. Verification in referral-based crowdsourcing. PloS one. 2012;7(10):e45924.

[36] Douceur JR, Moscibroda T. Lottery trees: motivational deployment of networked systems. In: ACM SIGCOMM Computer Communication Review; Vol. 37. ACM; 2007. p. 121–132.

[37] Naroditskiy V, Stein S, Tonin M, et al. Referral incentives in crowdfunding. In: Second AAAI Conference on Human Computation and Crowdsourcing; 2014.

[38] Hamilton M, Salim F, Cheng E, et al. Transafe: a crowdsourced mobile platform for crime and safety perception management. In: 2011 IEEE International Symposium on Technology and Society (ISTAS); May; 2011. p. 1–6.

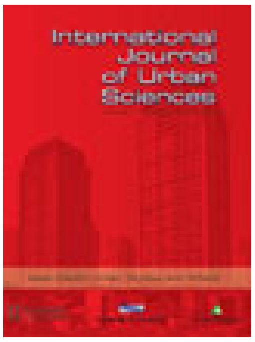
[39] Anna M, Sakhi Women's Resource C. A Safetipin for Our Cities: Research Findings of the Study Conducted in Thiruvananthapuram, Kerala 2014. Sakhi Women's Resource Centre; 2014. (Trivandrum, India); Available from: https://books.google.co.th/books?id= PMIOnQAACAAJ.

[40] Naik N, Philipoom J, Raskar R, et al. Streetscore - Predicting the Perceived Safety of One Million Streetscapes. In: Proceedings of the 2014 IEEE Conference on Computer Vision and Pattern Recognition Workshops; Washington, DC, USA. IEEE Computer Society; 2014. p. 793–799. Available from: 10.1109/CVPRW.2014.121.

[41] Ordonez V, Berg TL. Learning High-Level Judgments of Urban Perception. 2014. Avail- able from: 10.1007/978-3-319-10599-4_32.

[42] Porzi L, Bulò SR, Lepri B, et al. Predicting and Understanding Urban Perception with Convolutional Neural Networks. In: Proceedings of the 23rd ACM International Con- ference on Multimedia; New York, NY, USA. ACM; 2015. p. 139–148. Available from: 10.1145/2733373.2806273.

[43] Braun V, Clarke V. Using thematic analysis in psychology. Qualitative research in psy- chology. 2006;3(2):77–101.



International Journal of Urban Sciences

ISSN: 1226-5934 (Print) 2161-6779 (Online) Journal homepage: https://www.tandfonline.com/loi/rjus20

Exploring incentive mechanisms for mobile crowdsourcing: sense of safety in a Thai city

Jurairat Phuttharak & Seng Loke

To cite this article: Jurairat Phuttharak & Seng Loke (2019): Exploring incentive mechanisms for mobile crowdsourcing: sense of safety in a Thai city, International Journal of Urban Sciences

To link to this article: https://doi.org/10.1080/12265934.2019.1596038

Published online: 24 Mar 2019.

INTERNATIONAL JOURNAL OF URBAN SCIENCES
https://doi.org/10.1080/12265934.2019.1596038

Exploring incentive mechanisms for mobile crowdsourcing: sense of safety in a Thai city

Jurairat Phuttharak [a] and Seng Loke[b]

[a]Department of Management Information Technology, Prince of Songkla University (Trang Campus), Trang, Thailand; [b]School of Information Technology, Deakin University (Burwood Campus), Melbourne, Australia

ABSTRACT

The rapid adoption of mobile devices enables capture and transmission of a variety of sensor and user-contributed data, creating a new data collection paradigm and a wide range of services, often termed as mobile crowdsourcing. However, we are still investigating factors contributing towards the effectiveness of such systems. One key factor to succeed in mobile crowdsourcing applications is the incentive mechanism, which motivates people to contribute to a crowdsourcing effort. In this research, we conducted field experiments that compared the effectiveness of non-monetary and monetary incentive mechanisms, using both quantitative and qualitative methods. The focus was on an exploration of how these mechanisms motivate users' performance in a mobile crowdsourcing environment. In the experiment, we developed a smart zoning application that allows users to share areas of the cities they perceived as safe or unsafe. The results from this study contribute to research in mobile crowdsourcing for urban understanding. Taken together, these results suggest that payment-related incentives can not only engage people's interest in project participation but also help improve their work performance in terms of productivity and quality. Notably, a fixed-price financial reward mechanism is best suited for short period data collection and achieving data quality. Also, referral incentive mechanisms, if properly designed, have the potential to extend user coverage, both spatially and temporally. These results can be helpful with regard to the formulation of guidelines on how to create and organize effective payment-based incentives for crowd involvement in cities.

ARTICLE HISTORY
Received 8 September 2018
Accepted 9 March 2019

KEYWORDS
Incentive mobile crowdsourcing; incentive mechanisms; sensing safety in cities

1. Introduction

There has emerged a new computing approach that employs human abilities to perform the tasks combined with machine computation. This new mode of human involvement with machine is called *crowdsourcing*. Crowdsourcing is an approach to outsourcing tasks to be carried out by crowds reachable through the Internet. Examples of such tasks are those related to the areas of sentiment analysis, natural language understanding, image recognition and creativity (Yuen, Chen, & King, 2009; Yuen, King, & Leung, 2011).

CONTACT Jurairat Phuttharak jurairat.b@psu.ac.th Department of Management Information Technology, Prince of Songkla University (Trang Campus), Trang 92000, Thailand

These kinds of tasks require high accuracy and efficiency. Although many previous studies have focused on increasing the performance of machine-based computational systems and using sophisticated algorithms and computing architectures to solve complex problems, there are a large number of tasks that currently cannot be accurately and efficiently performed by machines (Quinn & Bederson, 2011). These tasks are better suited to humans who are innately good at creativity, visual processing, planning, and analysis tasks. Hence, humans can perform them easily with high accuracy and efficiency. Recently, the rapid diffusion of crowdsourcing technologies has been seen both in industry as well as in academia (Morschheuser, Hamari, & Koivisto, 2016). Large companies exploit the benefits of crowdsourcing such as seeking ideas from the crowd. Dell[1] gathered ideas from various groups of people, either inside or outside their company, to make a good decision on how to design their new products to most satisfy future customers. Other examples of similar exploitation are particular cases of the well-established firms that include Threadlesss,[2] iStockphotos,[3] and InnoCentives.[4]

The applications of crowdsourcing are not restricted only to business, but it can also be applied to the areas of scientific research and engineering, such as volunteered geographic information (Goodchild & Glennon, 2010), the cultural heritage domain (Oomen & Aroyo, 2011), and the public health ecosystem (Swan, 2012). Notably, a growing segment of mobile phones is turning to ubiquitous computing. Mobile phones are increasingly able to sense a variety of modalities; for example, mobile devices recording text, images, and location information. It is referred to as participatory sensing, when users are involved in deciding what data to collect. In recent years, mobile crowdsourcing applications have emerged and become a potential device for business and society (Chatzimilioudis, Konstantinidis, Laoudias, & Zeinalipour-Yazti, 2012), and for smart cities (Mata et al., 2016). Sensing applications using crowd-powered computing (Franke, Lukowicz, & Blanke, 2015; Guo, Chen, Zhang, Yu, & Chin, 2016; Wang, Zheng, Zhang, Wang, & Shen, 2016; Zheng et al., 2016) are designed for monitoring purposes in different situations, such as monitoring movement patterns (e.g. running, walking) in common activities and monitoring traffic congestion and air pollution levels in an intelligent transportation system of smart cities.

The deployment of crowdsourcing applications in the real world faces several challenges such as power consumption related to the extra burden of sensing and transmitting, user's location privacy concerns, and integration of sensing information from different sources types (Vergara-Laurens & Labrador, 2013; Vergara-Laurens, Mendez-Chaves, & Labrador, 2013; Yerva, Jeung, & Aberer, 2012). However, the success of crowdsourcing applications depends on the number of participating users. Sustainability of a crowdsourcing application also depends on the volume of consistent users' participation. Thus, it is important to ensure that necessary elements with the abilities to attract and sustain users' participation are embedded into the crowdsourcing applications. One of these elements is an incentive or motivation. Incentive mechanisms are considered as necessary to increase user participation in a crowdsourcing task. To be attractive and appealing, the incentive mechanism has to be designed according to users' preferences.

The incentive mechanism is the recruitment strategy which requires users to contribute to crowd tasks in crowdsourcing systems. Doan, Ramakrishnan, and Halevy (2011) discussed crowdsourcing systems on the web from a variety of perspectives. They introduced the nature of collaboration on crowd contribution in two aspects: internal factors, such as learning and boredom, and external factors like the provision of monetary interventions. Monetary incentives were found to be the most important factor for participation in the software development crowdsourcing domain (Kaufmann, Schulze, & Veit, 2011). Much work (Cebrian, Coviello, Vattani, & Voulgaris, 2012; Kaufmann et al., 2011; Mason & Watts, 2009) has suggested that workers perform better when offered performance-contingent financial incentives.

In this research, we investigate the use of incentive mechanisms based on the monetary approach, comparing it with non-monetary approaches. The question of whether different incentive mechanisms impact upon users' decision on working tasks using mobile crowdsourcing applications is addressed. We consider micro payment models with different set amounts per sample and referral-based payment models with low and high levels of such incentives for direct referrals. These incentive schemes are compared to the base case of no additional incentive mechanism for the data collection as a whole. We define a set of metrics that can be used to evaluate the effectiveness of incentives and report findings derived from a pilot study using various monetary incentive mechanisms in sustainable smart city crowdsourcing applications.

In particular, our application involves crowdsourcing feelings of safety about CBD locations in a Thai city. Thai people may not be familiar with the term 'crowdsourcing', but they may actively engage with its process in their daily life activities; e.g. sharing the files, video clips or even their ideas/opinions via social media (Leesa-Nguansuk, 2018). In the study, we also discuss both quantitative and qualitative evidence on the effectiveness of the different motivations and strategies. The results contribute to the area of mobile crowdsourcing by proposing the design guidelines and mechanisms on how to create and organize effective payment-based incentives with crowd involvement.

2. Related work

Mobile crowdsourcing enables the pervasive use of smartphones and other resource-rich devices to create a wide range of services, from community sensing (Guo, Dai, et al., 2016; Mata et al., 2016; Murphy & King, 2016; Wang et al., 2016) to wireless network characterization (Naito, Tani, & Takai, 2016) and micro-task markets such as Amazon Mechanical Turk (AMT)[5] and Micro-Workers.[6] Although the capabilities of mobile crowdsourcing services are increasing, the effectiveness of such systems has been claimed to critically depends on the willingness of their user's participation. For mobile crowdsourcing services to be successful, one must provide effective motivators to engage motivate a large number of individuals to participate.

Incentive mechanisms are one of the most critical factors for motivating people to contribute to a crowdsourcing effort (Chatzimilioudis et al., 2012; Jaimes, Vergara-Laurens, & Raij, 2015). The use of effective recruitment strategies is needed to actively engage and motivate people to contribute to crowdtasks in crowdsourcing systems. Kaufmann et al. (2011) explore the workers' motivation in crowdsourcing. According to their study, motivating factors are categorized into intrinsic (e.g. enjoyment and community motivation) and extrinsic motivations (e.g. immediate payoffs, delayed payoffs, social motivation). Intrinsic motivation exists if an individual's act on the activity is driven by internal factors, e.g. acting just for fun or enjoyment. Differently, in achieving a certain desired outcome, behaviour of an extrinsically motivated person is driven by the external instrument; e.g. acting for money or avoiding sanctions. In addition, a recent survey on incentive techniques in participatory sensing can be found in (Jaimes et al., 2015). The authors classify a taxonomy of crowdsourcing incentive mechanisms. Based on the types of stimuli that encourage user participation, this research identifies two large branches: monetary and non-monetary incentives. Monetary incentives can be either static or dynamic, whereas incentives for non-monetary mechanisms incentives include collective motives, social rewards, and intrinsic motives. Since AMT has used micro-payments as incentive tools for task fulfilment, they are several studies that have studied the use of monetary rewards to provide appropriate incentive to the participants. Mason and Watts (2009) showed that higher micro-payments led to higher task completion rates on AMT but does not necessarily improve quality. Similarly, Heer and Bostock (2010) used AMT to conduct a visualization study and found that larger incentives led to faster completion times but no difference in the quality of data provided across different incentive amounts. Reddy, Estrin, Hansen, and Srivastava (2010) use five types of micropayments including macro, low, medium, high, and complete micropayments; their findings showed that the method used to estimate the payment affects participation level and data quality.

Micro-payments are being increasingly used in mobile crowdsourcing. The studies in incentive for mobile crowdsourcing can be classified into two groups: (1) applicationindependent incentive mechanism and (2) specific application scenario. For the first group, most studies target properties such as cost minimization, utility maximization, and fairness. Koutsopoulos (2013) designs an incentive mechanism based on optimal reverse auctions in order to minimize the total compensation cost but it still keeps participants motivated. Naito et al. (2016) also study micro-payment incentives in the context of participatory sensing. Their study tested multiple micro-payment amounts as well examined how game-like characteristics affect compliance and data quality. Yang, Xue, Fang, and Tang (2012) propose the models for incentive design including platform-centric and user-centric models. In the platform-centric model, the crowd takes the incentive mechanism as a Stackelberg game to maximize the utility. Another approach is an auction mechanism which derives a truthful cost declared by participants.

The second group of research on incentives for mobile-based crowdsourcing aims to develop specific application scenarios and considers incentive design as part of the application. For example, in the CrowdPark system (Yan et al., 2011), the author designed a protocol for drivers to buy and sell information about parking vacancies from and to others. The findings showed that drivers are able to receive better compensation when they follow the trading protocol and carefully configure the incentive parameters. In a similar study, Liu and Chen (2014) proposed a pattern to design a crowd-based system for realizing smart parking by mobile crowdsourcing. The application is able to recruit drivers to collect information about parking occupancy and use these data to help drivers find proper parking vacancies efficiently. Their findings showed that when only useful data is rewarded, they are able to encourage participants to contribute not only their sensor data but also their intelligence in the problem-solving process. Moreover, in (Deng & Cox, 2009), the authors developed an application for sharing pictures of price tags by providing contributors with pricing information in nearby grocery stores.

Referral or viral marketing is a highly sought-after way of advertising. This technique has received a lot of interest in the theoretical community. Kleinberg and Prabhakar

(2005) study a model where incentives must be provided for users to propagate a question until a node that knows the answer is reached, and Cebrian et al. (2012) considered the use of recursive mechanisms in this context. Naroditskiy, Rahwan, Cebrian, and Jennings (2012) provided a theoretical justification for the recursive mechanism used in the DARPA Network Challenge, and desirable properties of a referral scheme have been posed in (Douceur & Moscibroda, 2007). However, these studies concentrate on theoretical issues and do not investigate or compare referral mechanisms empirically with real users. There is little existing empirical work on comparing incentives for referrals on mobile based crowdsourcing. Recently, Naroditskiy et al. (2014) conducted a field experiment in the referral incentive in crowdfunding, where a field experiment was used to compare several mechanisms for incentivizing social media shares in support of a charitable cause. Under the control treatment, no extra incentive is provided. Under two of the other mechanisms, the sharers are offered a fixed number of points (1 extra point and 3 extra points) that help take the campaign further. The authors find that the 3-point mechanism is more effective than the 1-point mechanism. This is contrary to the intuition that it is not the exact value, but rather the presence of some form of incentives, which has the most effect.

Recently, crowdsourcing has been widely used for gathering public perceptions of safety or crime across in cities across the world. Hamilton, Salim, Cheng, and Choy (2011) proposed a mobile crowdsourcing platform called Transafe that captures and analyses the safety perceptions for people travelling on public transportation in Melbourne, Australia. Their framework enables the users to report crimes/misdemeanours and provide information about transportation and emergency services around where the users are located. In their work, the crowd voting mechanism has been used to aggregate people's feelings of a particular place. Safetipin (Anna, 2014) is another platform which used crowdsourcing to generate safety information about a city. This platform used parameters such as lighting, transportation, feeling of safety etc. to generate a safety score for a particular area. This safety information has been gathered through community volunteers and partnership with NGOs. Recent work such as (Naik, Philipoom, Raskar, & Hidalgo, 2014; Ordonez & Berg, 2014; Porzi, Bul, Lepri, & Ricci, 2015) has proposed computational methods to automatically infer high level perceptual attributes from geo-referenced images of urban spaces. Such work converted the pairwise comparisons for perceived safety to ranked scores and trained a regression algorithm using generic image features to predict the ranked score for perceived safety. Such work did not focus on incentive methods to motivate people to contribute towards a crowdsourcing effort. Our study explores micro-payments for mobile sensing tasks together with a referral incentive technique. We also analyse the effects of different payment schemes on participation frequency, quality, monetary cost and coverage; also, our work, we believe, is novel in crowdsourcing the sense of safety in a part of a city in Thailand.

3. Crowdspots deployment and study details

The perception of safety is important as it influences how people feel and behave towards their surroundings. Hence, we developed a mobile application that can contribute to empowering people in voicing their feelings (and so, they may feel safer) by enabling reporting of safe and unsafe spots in a part of a city in Thailand. In Thailand, road traffic accidents are one of the major causes of deaths. Thailand has a road traffic death rate of 36.2 per hundred thousand population, compared to the global rate of 17.4. Hence, it is not just crimes but also traffic that can cause one to feel unsafe at a particular spot. And the local media reports that a high percentage of commuters feel unsafe and vulnerable when they travel.

For our experiment, we have developed a mobile app that allows participants to take photos of target places and geo-tag their photos on a map called Crowdspots. In this section, we first outline key characteristics of the Crowdspotsmobile crowdtasking platform. We then describe the contexts applied to the mobile crowdsourcing experiment as well as the system used in the study. Finally, deployment setup details along with metrics to evaluate incentive models are provided.

Crowdspotsallows crowd workers to share information about particular areas of the city they consider as either safe or unsafe with location-based reporting tasks. Figure 1 shows the screenshots for the Crowdspots application. The architecture of Crowdspots is organized as a client-server model composing of participants/clients and a backend system/server. Clients refer to any participants working to respond to the tasks via mobile devices. Their functions are to capture and provide the user's interface. The backend-system is for data storage, processing and visualization. There are two types of users involved in this platform: (1) crowd workers/users and (2) the administrator. Workers will be asked to perform the tasks by taking geo-tagged photos of target places. The administrator views and approves photo contributions. The rewards will be finally granted by the administrator for quality tasks performed by individual workers.

3.1. Experimental design

The main purpose of this study is to investigate the effectiveness of different incentive treatments for encouraging participants to perform certain tasks. We undertake an experiment where the participants' performance of task completion was tested using four mechanisms that differ in the way they are incentivized. In completing the tasks, the participants were required to report spots they perceived as safe or unsafe in one CBD area, together with geo-tagging them on a map. The mechanisms offered a certain reward for spots reported. The reward was expressed in terms of incentivized payment and differs across the mechanisms as follows:

(1) Fixed-price payment – Participants are given 5 baht (20 Australian cents) for every single task they completed. Extra rewards worth 2 baht are offered only in case they add the caption to each photo. (1 AUD = 25 Baht);
(2) Low-price referral payment – Participants are offered the same payment rate as those in the fixed-price payment group. Extra payment of 5 baht will also be awarded to them for successfully referring each person to complete the task;
(3) High-price referral payment – Apart from being given 5 baht for each task, the participants will receive an extra reward of 75 and 200 baht for successfully referring 10 and 25 people respectively to complete the task; and
(4) Non-payment– Non-monetary incentives are provided for participants in this group. Their participation is volunteer-based and thus taken as a base case treatment.

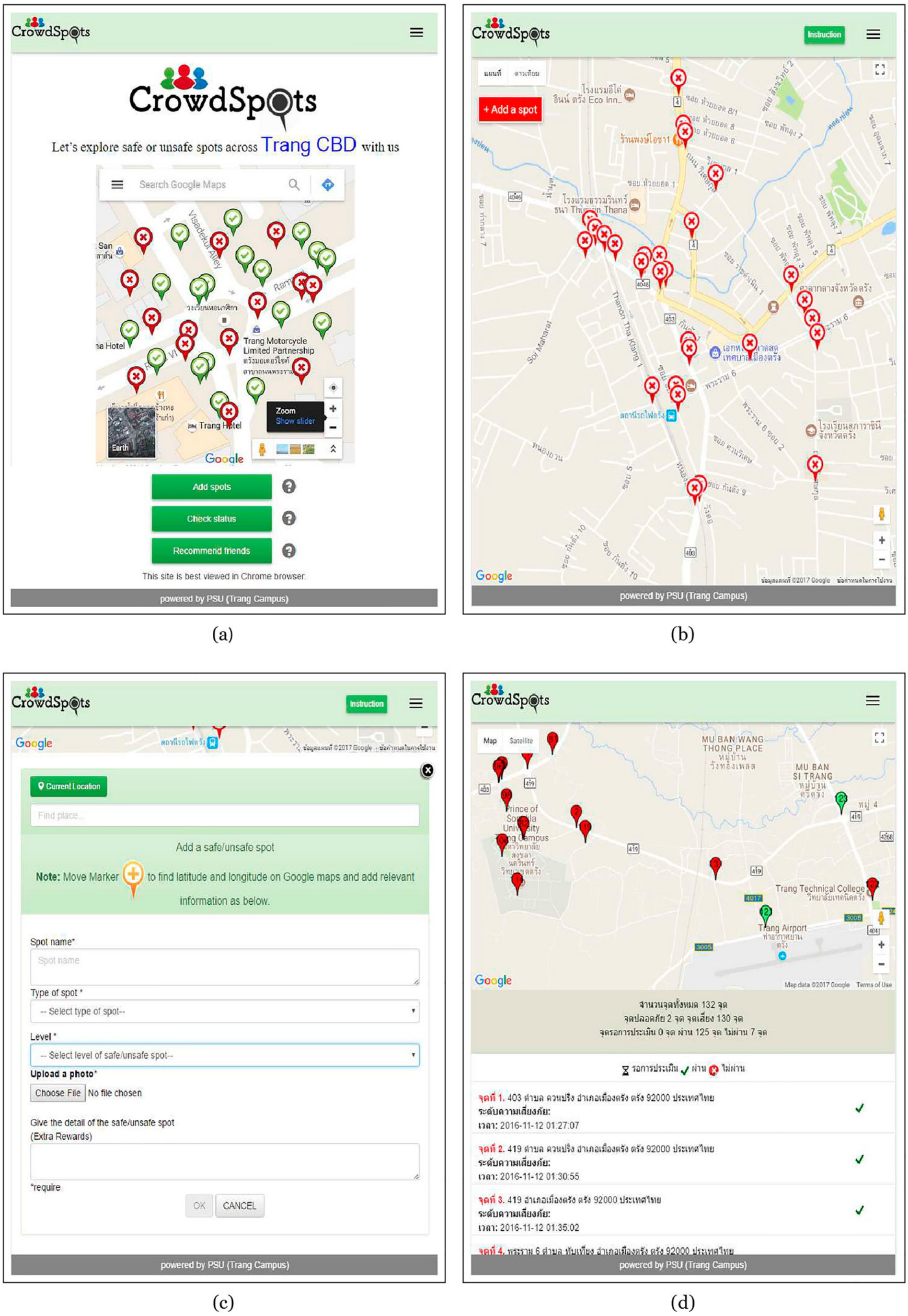


Figure 1. Screenshots from left to right: (a) crowdspots main screen, (b) a map showing some areas of the city mapped by participants, (c) the submission screen, (d) the financial board with points and financial tall.

Based on the incentive mechanisms mentioned above, participants were divided into two main groups: an experimental group and a control group. The participants exposed to the first three monetary incentives were put in the experimental groups, whereas the ones with non-payment are the control group.

The Crowdspots application was deployed by participants for a week, starting from the middle of the week (Wednesday). The participants were asked to tag geo-locations and capture images of places. Prior to starting work, the participants were informed about the purpose and length of the study, trained on how to tag and collect images, and informed only about the specific incentive they belonged to. They were also asserted that only clear (not blurry or too dark) images of place contents that were considered as valid and will consequently be rewarded for. Collecting data on the same place by the same user was not allowed. Under referral mechanisms, the participants who referred tasks to others would receive extra rewards only when their referrals signed up to the application, together with generating a successful given task. Importantly, any referrals would receive the same incentive as the original groups of participants.

3.2. Participant recruitment

The strategies we used to recruit participants in this study were guided by the study purpose and design. As the study aims at comparing four treatments that differ in the incentivized mechanisms, both paper and electronic versions of advertising flyers were distributed throughout one university to approach participants. There were two phases of task-related advertisement, non-monetary and monetary. In the non-monetary tasks phase, individuals were made clear that no monetary rewards were given for working on tasks so that they could to determine if they were willing to assist with recruitment efforts. People of the other phase were told about being paid after completing tasks. Upon completion of the recruitment process in the monetary task phase, the participants were randomly assigned to each of the three treatments (the experimental groups). The participants were affirmed that their decision to participate or not to participate would not affect their relationship with the researchers and the university in any way.

In this recruitment process, we decided to set the number of participants to be equal for each treatment. This decision not only made fair and reliable comparisons of effectiveness of the treatments but also enabled us to manage a budget more effectively. Ten students who responded to the call for participation in each treatment were then recruited for initial work. Since referral mechanisms allow invitations of other people, an additional 74 participants were recruited. There was thus a total of 114 participants used for quantitative data analysis.

3.3. Measurement parameters

There four key performance metrics of interest to mobile crowdsourcing: quantity, quality, area coverage and cost.

- *Quantity* – It represents the number of tasks that are completed by participants. It can be compared over different time intervals during the data collection period (for instance, submission per hour or day).

- *Quality* – The quality is measured by the participants' abilities in capturing the photos of the target places. In other words, the completeness of tasks captured is indicative of the quality whether the photos captured are totally incomplete or partly complete (e.g. a mismatch between a place captured and its photo or the amount of image noise). In this regard, the percentage of invalid photos of the places (e.g. whether they are blurred or too dark to see) are calculated, together with the calculation of the percentage of optional annotations provided as captions on the photos. Three people were invited to evaluate the quality; two are people who are familiar with the areas investigated due to their daily commuting and the other is a government official whose work is related to provincial transportation and security.
- *Area coverage* – This refers to the spatial and temporal extent associated with samples provided by participants.
- *Monetary cost* – This cost refers to the total earnings of all users in three different groups of participants using different incentive approaches, i.e. the estimated expenses the researcher has to pay these participants for the responses (i.e. tasks) they provide.

3.4. Statistical analyses

Both descriptive and inferential statistical tests were carried out in this study. First, the simple statistical test (i.e. the means, modes, frequencies and percentages) was intended to describe participants in terms of the number of tasks completed and the number of invalid data created in each of the approaches. Second, the inferential statistical test was used to examine whether there were any significant differences in the four key performance metrics (as mentioned in the section above) across the four incentives to mobile crowdsourcing. To compare the differences in medians among four student groups, we used Kruskal–Wallis analyses of ranks. This test is considered as appropriate to the current study since it can determine the significance of difference among the three groups even when the distribution of the data is not normal. All tests of significance used two-tailed p values. Specific group differences were examined by using post-hoc non-parametric group comparison method. Throughout the study, the alpha level for tests of significance was set at $\alpha < 0.05$.

4. Quantitative results and analysis

In this section, we analysed the results from our data collection. For our experiment, quantity was defined by the total number of photos and tag geo-coordinate on the map submitted by the participants for a week. Quality was measured by analysing the percentage of correctness of the photos submitted, together with calculations on percentage of optional annotations provided with the captions on the photos. Coverage was computed by taking into account the number of spatial blocks and temporal periods of the participants. Frequencies of data across the four groups were compared using chi-square analysis. Since the behaviours within each group did not follow a normal distribution, the non-parametric Kruskal–Wallis test was carried out to test significant differences between the groups, using two-tailed p values. Specific group differences were finally examined by post-hoc non-parametric group comparison methods. Bonferroni correction was used because it is highly flexible, simple to compute and can control for inflating Type I errors (i.e. the bias caused by multiple comparisons).

Overall, Crowdspotsproved very successful in allowing us to map and monitor safe or unsafe areas around Trang CBD. Over a week, the participants made 500 recordings in total and added safe/unsafe spot areas to the database. As illustrated in Figure 1(b), this resulted in a detailed mapping of safe and unsafe spot areas in the Trang city centre. And the participants were between 17 and 25 years old. Table 1 shows the total number of participants using each of the incentive mechanisms, together with the total number of outputs submitted by the participants, expenses, correctness and optional captions on the photos. To analyse the characteristics of different incentive plans, the results are described according to the key performance metrics of interest to mobile crowdsourcing in the following section.

4.1. Participation

The number of submissions made under each of the incentive types is shown in Table 1. It was clearly seen that the low-price referral method achieved the highest number of participants and task submission whereas the least successful one was the non-monetary model. The finding showed that the highest number of output tasks (175 tasks submitted) is derived through the use of low-price referral approach. Meanwhile, the number of participation output in the high-referral and fixed payment are 146 and 132, respectively. Remarkably, the non-payment approach is the least popular; just only 47 tasks were completed by participants. Although low-price referral treatment had the highest output, the individual user participation rates varied greatly.

Due to a lack of a normal distribution of the data, the non-parametric Kruskal–Wallis Test was carried out to test the differences in incentives between the groups. The result showed a statistically significant difference in the number of data collection output among the different incentive treatments, $\chi^2 = 20.41$, $p = 0.00$, with a mean rank score of 67.80 for non-payment, 107.15 for fixed-price, 54.80 for low-price referral and 58.44 for high-price referral method. We then conducted the post-hoc Kruskal–Wallis Tests, with results from Bonferroni correction displayed in Table 2.

When we conducted post-hoc analysis to test pairwise multiple comparisons. Findings suggested that the location tagging and photos added by a participant from the fixed-price group were significantly greater than those in the low-price referral ($p = 0.00$) and high-price referral ($p = 0.00$) groups. Consider the average of task submissions per person in the fixed-price group that was 13.2 whereas those in low-price and high-price approach were only 3.07 and 3.24 respectively (see in Table 3). Moreover, findings showed that there was no significant difference in performance of the participants of the fixed-price

Table 1. The total number of participants, task submitted, expenses, correctness and photo description by each group.

Incentive Method	Participants	Tasks Submitted	Total Expenses	Correctness	Photo Description
Fixed-price	10	132	875	125	130
Low-price referral	52	175	1260	164	171
High-price referral	45	146	1059	137	142
Non-payment	7	47	–	38	35

Table 2. The post-hoc results of participants' submissions with Bonferroni correction.

Sample1–Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.
Low referral – high referral	−3.646	6.869	−.531	.596	1.00
Low referral – non payment	13.002	11.809	1.101	.271	1.00
Low referral – fixed price	52.352	11.809	4.433	.000	.000
High referral – non payment	9.356	12.042	.777	.437	1.00
High referral – fixed price	48.706	12.042	4.045	.000	.000
Non payment – fixed price	−39.350	15.404	−2.554	.011	.064

and non-payment groups. However, the higher number of task submissions in the fixed-price group outperformed the non-payment group. It should be also noted that the mean in the fixed-price group (13.2) is greater than that of non-payment group (4.7) and the median of the fixed-price group (12.5) also is higher than of non-payment group (3.0). These values are shown in Table 3.

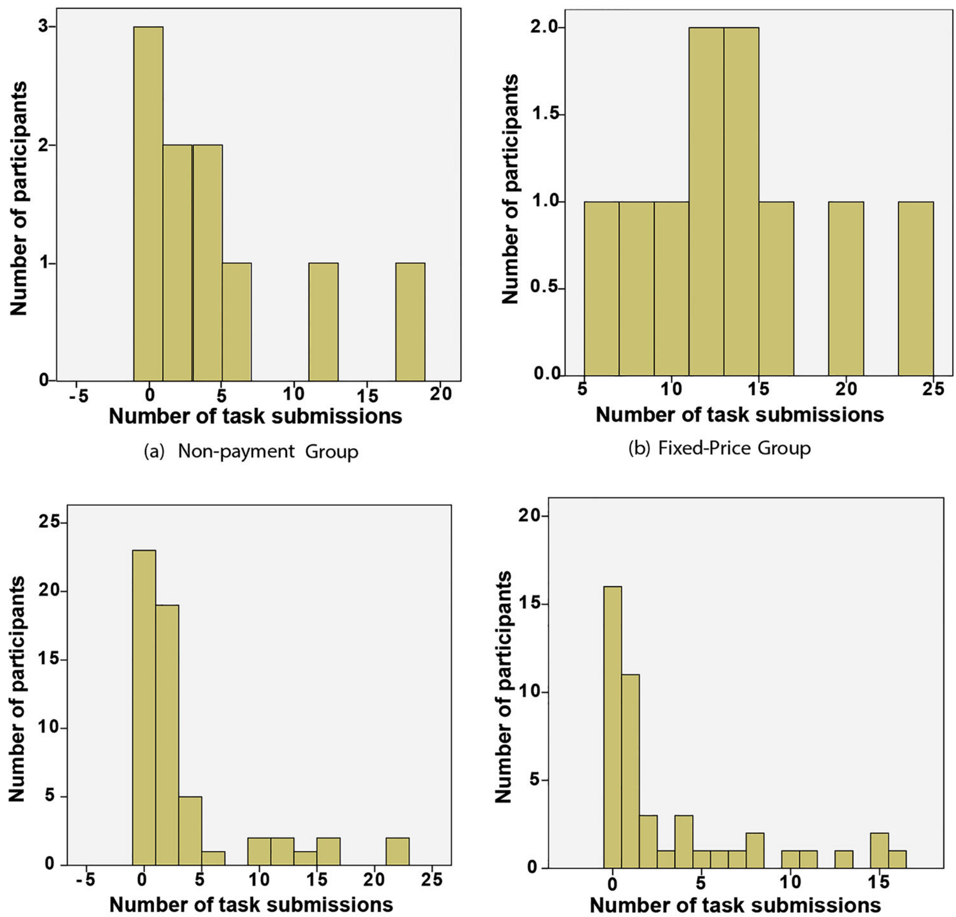
Although the number of outputs of participants of both low and high price referral incentive types was much greater than that of the non-monetary group (see in Table 3), the result showed that there was no statistically significant difference across the non-payment, low-price referral and high-price referral groups. The low-price referral group received the highest number of participant responses, but this group had the smallest score (3.07) as compared with other counterparts. Similarly, the mean of high-referral (3.24) was found to be slightly different from those of the low-price referral group. The report also showed the medians of both groups (low and high price referral = 1) was less than the median of the non-monetary group (3).

To further investigate the above issues, we decided to compare the data distribution of individuals in each group. The frequency distribution of all participant submissions was then plotted (see Figure 2). Results showed that the frequencies of low and high price referral groups were not normally distributed, and they were mainly distributed with value near 1. When looking into details of the participant data, we found that task submissions by 1 response had been mostly done by the people who joined via a referral. Here, it is interesting to note that there are two participant groups: (1) an invited group and (2) a referral group. The invited group refers to original participants who were recruited into the study and randomly assigned into each treatment, whereas the participants who obtained tasks through the direction of the invited participants fell into the referral group (only low and high price referral groups).

Table 4 shows the percentage of the number of participants and data collection out-put by each type of participants. Participants with low and high price referral types were offered the extra reward in the case that they could invite other people to complete the tasks. The results showed that the percentage of the number of referral participants (80.8% and 79.5%) was much greater than that of the invited participants (19.2% and 20.5%) in low and high price referral groups. In contrast, the number of submissions

Table 3. Overall data collection participation submissions.

Incentive Methods	Total	Mean	Median	Min	Max
Fixed-price	132	13.2	12.5	6	23
Low-price referral	175	3.07	1	0	21
High-price referral	146	3.24	1	0	16
Non-payment	47	4.7	3	0	18



(a) Non-payment Group
(b) Fixed-Price Group
(c) Low-Price Referral Group
(d) High-Price Referral Group

Figure 2. The frequency distribution of the number of participant submissions by each group.

by referral participants (24% and 30.1%) was less than the percentage done by invited participants (76% and 69.9%) for low and high referral groups, respectively. Overall, both of the low and high price referral incentive approaches appeared to motivate the higher invited participants, but it demotivated the majority of the referral participants. This issue was further investigated and analysed using data from semi-structured interviews (see the detail in Section 5).

Table 4. The percentage of the number of participants and data collection output by each type of participants.

Incentive Methods	Num. of invited participants (%)	Num. of referral participants (%)	Num. of submission by invited participants (%)	Num. of submission by referral participants (%)
Low-price referral	19.2	80.8	76	24
High-price referral	20.5	79.5	69.9	30.1

Table 5. The post-hoc results of output quality with Bonferroni correction.

Sample1–Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.
Low referral – high referral	−3.780	6.843	−.552	.581	1.00
Low referral – non payment	12.002	11.764	1.020	.308	1.00
Low referral – fixed price	52.752	11.764	4.484	.000	.000
High referral – non payment	8.222	11.996	.685	.493	1.00
High referral – fixed price	48.972	11.996	4.082	.000	.000
Non payment – fixed price	−40.750	15.345	−2.656	.008	.048

4.2. Quality

The quality of data derived from using different incentive models was analysed. Results from the Kruskal–Wallis Test revealed that there was a significant effect of correctness of task submissions across the different incentive mechanisms, $\chi^2 = 20.75$, $p = 0.0$, with the mean rank scores of 66.80, 107.55, 54.80, and 58.58 for groups of non-monetary, fixed-price, low-referral and high-referral, respectively. We then conducted the post-hoc Kruskal–Wallis Tests, with Bonferroni correction. The results were displayed in Table 5.

The finding showed the correctness of the fixed-price group was significantly greater than in those of the non-payment, low-price referral and high-price referral groups. Nevertheless, there was no significant difference in the correctness among non-monetary, low-price referral and high-price referral groups. We also explored the validity of task submissions; that is, it was to check whether the photos captured were totally incomplete or partly complete; e.g. a mismatch between a place captured and its photo (invalid coordinates) or the amount of image noise (blurred or too dark to see, invalid photos). In this regard, the percentage of invalid photos of the places was calculated. Based on the number of output errors, the percentages of them were displayed in Table 6. It was clearly shown that the non-monetary method had the largest percentage of invalid output (19.2%) whereas the fixed-price method received the least of errors (5.3%). In addition, the errors caused by the invalid photo were found to be more common than the errors by invalid coordinate in all four groups. Features of the invalid photos include poor quality of the photos taken (too dark or too bright) and imprecision of unsafe/safe spots focused on.

The participants can get extra rewards by adding a caption to each of the photos. The percentages of photo description are presented in Table 7. The results showed that participants mostly provided the captions of the images. Remarkably, the smallest percentage fell

Table 6. The percentage of overall error, invalid photos and invalid coordinates by each group.

Incentive Methods	Overall error (%)	Invalid photo (%)	Invalid coordinates (%)
Fixed-price	5.3	71.43	28.57
Low-price referral	6.3	63.64	36.36
High-price referral	6.2	66.67	33.33
Non-payment	19.2	75.00	25.00

Table 7. The percentages of photo description by each group.

Incentive Methods	Num. of optional description (%)
Fixed-price	94.70
Low-price referral	91.43
High-price referral	93.84
Non-payment	74.47

in the non-payment group (74.47%), whereas the percentages of the three counterparts were found to be higher 90%.

4.3. Monetary cost

The cost/expense used in this study refers to the total amount of money paid to the participants for the completion of crowd tasks performed. The total expenditures for each crowdsourced experiment have been shown in Table 1. The result showed that the highest cost fell in the low-price referral treatment (1,260 baht), followed by the high-price referral group (1,059 baht) and the fixed-price group (875 baht). When using a Kruskal–Wallis Test to find association of rewards among experimental incentive techniques, we found that there was a statistically significant difference in the rewards (participants' income) offered to the participants using different incentive treatments, $\chi^2 = 29.73$, $p = 0.00$, with a mean rank reward score of 26.50 for non-payment, 107.60 for fixed-price, 58.39 for low-referral and 62.97 for high-referral methods. We then conducted the post-hoc Kruskal–Wallis Tests, with results from Bonferroni correction displayed in Table 8.

Results from the post hoc comparison revealed significant differences in five pairs of incentives: (1) non-payment and fixed-price group, (2) non-payment and low-price referral, (3) non-payment and high-price referral, (4) low-price referral and fixed-price group and (5) high-price referral and fixed-price group, indicating that different incentives impact upon how different the earnings would be. It should also be noted that the finding shows the highest earnings fallen in the fixed price payment, probably suggesting that when earnings or rewards are under the participants' own control (they could make their own decisions on how much work to be completed, as in fixed-price group), rather than being dependent on others (as in two referral groups), they are likely to be more engaged or more active in working on the tasks. No significant differences in earnings were found between low-price referral and high-price referral.

In addition, we analysed the correlation between earnings/rewards and correctness of the responses to investigate the relationship between them. We found a significant correlation between the earnings/rewards and quality of takes they submitted ($p < 0.05$). This means earnings/rewards are ones of effective incentives – the more earnings/rewards the participants receive, the higher the quality of their tasks is expected to be.

4.4. Coverage

In the study, the design that the participants were required to geo-tag photos for a week in Trang CBD allowing us to see various areas, either safe or unsafe, on a map. To analyse the coverage provided by participants, we plot the density of outputs/contributions on a heat

Table 8. The post-hoc results of monetary cost with Bonferroni correction.

Sample1–Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.
Non payment – low referral	−31.895	11.619	−2.745	.006	0.36
Non payment – high referral	−36.467	11.848	−3.078	.002	0.13
Non payment – fixed price	−81.100	15.156	−5.351	.000	.000
Low referral – high referral	−4.572	6.758	−.677	.499	1.00
Low referral – fixed price	49.205	11.619	4.235	.000	.000
High referral – fixed price	44.633	11.848	3.767	.000	.001

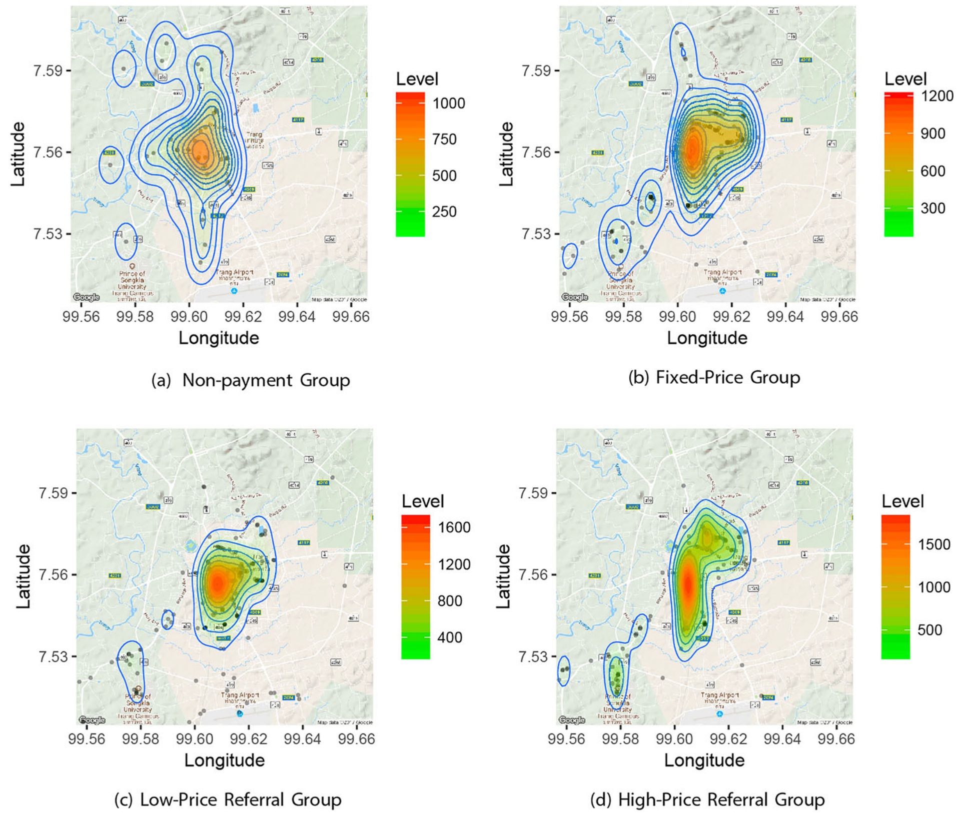


Figure 3. The heat map of each treatment.

map. The heat map for each incentive type is presented in Figure 3. In the heat map, we can see spots tagged by the participants. The density of those spots was identified by different colours 'red' for the highest density of tags and 'green' for the lowest density. The heat map indicates that low-price referral had the most coverage, followed by high-price referral and fixed-price incentive types, whereas the non-monetary group yielded the least coverage.

Furthermore, we investigated the different periods' tasks were being posted in a week by the participants from across four different incentives. As Figure 4 presents, there was no obvious difference in time periods the participants decided to post their tasks; that is, posting over the weekends seemed to be their most preferable time and the postings reduced by the end of the week.

5. Qualitative results and analysis

This section addresses participants' first-hand experience in using the application in this project and factors that motivate them to do tasks. The results presented in this section were derived from semi-structured interviews with 12 participants, three from each of the four groups.

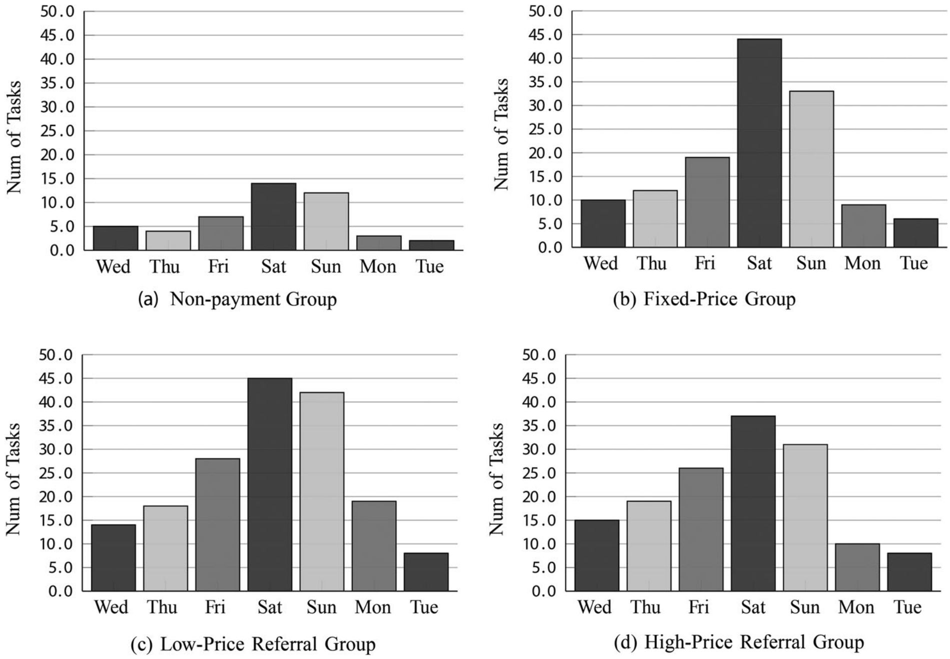


Figure 4. Daily task submissions in a week by the participants of across four different incentives.

The interviews were audio-recorded, transcribed verbatim and translated from Thai language to English. We then undertook a thematic analysis (Braun & Clarke, 2006). The key themes that emerged from the analysis are discussed below. The interview questions covered the participants' perception when they completed tasks using the application, i.e. their impression of (1) the application generally, (2) the usage of location information and images for task assignments, (3) satisfaction with incentives provided, (4) time and work management, and (5) other constraining factors.

5.1. Usability of the app

Most of the interviewed participants felt that the app was intuitive and easy-to-use. For example: 'I have no difficulties in the use, only three steps were needed to report the location and post the photo'. However, some participants seemed to suffer when they tried to upload photos because their photos were too big and took a long time for them to upload. Overall, it is unlikely that basic usability issues impacted on the results of our study.

5.2. Performance-related financial incentive

As shown in the previous section, all financial groups including fixed-price, low-price referral and high-price referral gathered a significantly greater quantity of data submissions, confirming that the financial incentive could motivate users far more than non-payment motivation did. However, this motivating effect came with a cost for the task provider, as shown in the findings. Interviewed participants in all financial groups were satisfied with the hiring rate, and they reported on their 100% willingness to do more. In contrast, there was only one non-payment participant who performed tasks without expecting payment who was willing to continue.

For incentive programmes, all interviewed participants were satisfied with both low and high referral approaches that made use of through friend connections or viral marketing. Some of their comments that reflect this satisfaction are: 'Encouraging friends to work on tasks is my way to earn more money', 'I've not found difficulties in inviting friends to join this job', and 'The more friends I can invite, the more money I can earn'. It appeared that most participants spread the word via their social networks, e.g. Facebook, Twitter or Instagram. They added that social networks made sharing information very easy and fast. In their opinion, posting tasks through social networks helped them reach a large audience with no need for providing detailed explanations. In addition, messenger or chat platforms were their preferred methods in distributing their messages towards targeted friends or people who may share similar interests.

5.3. Socio-cultural drives

The interview data revealed that all students in a non-payment group in particular reported on their willingness to participate in the task project. Their reasons for this participation appeared to arise from socio-cultural factors. The students' perceptions viewing the researchers as their former lecturer impacted upon their decisions to participate, as supported by their comments: 'I used to be your student in the previous courses' (Student A), and 'I'm feeling like it's a good opportunity for me to work with you and learn how to work from you', for instance. This finding can be partly explained through a socio-cultural lens. Thai traditional beliefs view teachers as the givers of knowledge and the second parents of students. The students in this study then regarded their participation as a way to express 'feelings of being grateful' to their teachers: 'You are my lecturer and would like to help you (to do this project)'.

Another factor that has influenced the participants to do tasks is a sense of collectivism, the idea that the individual's life belongs to a group. The interview data revealed that the majority of student participants who joined the project via referral approach was friends of friends. Following are some of the examples that illustrated this phenomenon: 'I decided to join this project because my friend requested me to do so', 'I just helped my friend. She posted on Facebook a request for this help'. This finding suggests that a sense of harmony and a high level of group orientation have a positive impact upon initial willingness to perform tasks. However, it seemed that the participants in referral groups failed to work actively on this project as only a few spots were tagged by them. This lack of active engagement was supported by the statement: 'I worked on this task just because of my friend's request'. This finding supports quantitative results; that is, the majority who joined the project through word-of-mouth tended to submit only few outputs. A possible explanation for these results may be the lack of internal motives; that is, the participants felt they were engaging in tasks because they were pressured by some other external factors (i.e. friends' request), rather than choosing to do so by themselves. As such, the ability to devote extra time to complete tasks is restricted, as evidenced in this study. There could also be other motivational factors, such as building the map as a reference to help improve safety in the area, but was not explored further in this study.

5.4. Working strategies

The interview data helps to explain results from the quantitative analysis that the least outputs were submitted by non-monetary participants. The participants in this group admitted that they would work on tasks only when 'time' and 'convenience' permitted: 'I had no class over the weekends and it's my free time' or 'I was about to visiting the places for my personal purposes' (e.g. dining and doing errands). In short, they had no goal-oriented intention to do the tasks, which certainly impact upon the number of tasks performed. Differently from the other three groups who were payment-related, they set plans for work and tried to make themselves more disciplined in achieving the tasks, as evidenced in some of their instances: 'I planned to work on tasks every day, two hours a day at least', 'My plan was to collect at least five points a day', and 'I tried not to give up my plan; I did it every day after class'.

Based on the results from the interviews, it should be noted that in all incentive mechanisms, there are similarities in terms of data collection behaviour. The participants mostly reported on spending their free time, especially during the weekend doing the tasks. By making a list of spots to investigate, many of them could not only maximize their time but also save cost: for example, 'I set a plan for places, safe or unsafe, to visit in particular so that I won't waste much money on fuel expenses', and 'I started working on things most familiar to me. I mean the places in my area. Rather than keep riding, I knew exact destinations. This helped save my time'.

A similarity in working behaviour was also mentioned regarding their data submission or posting. The participants started by taking photos of places investigated and recorded relevant data on either on mobile phones or notepaper. By the end of each day of data collecting, they would upload data (photos, captions, and relevant details) into the system using Wi-Fi available in their accommodations/university. These students tried to avoid using 3G/4G in data uploading in order to save costs: for example, 'I uploaded data every day at night through Wi-Fi of the university. This saved my money' and 'I would use 3G (in submitting tasks) only when Wi-Fi at home was very slow or didn't work'.

5.5. Constraints

Data from interviews enabled insight into constraints participants perceived while collecting data. 70% of the participants requested extending the period for collecting data. Some of their typical reasons for this request are: 'If I was given more time, like 2 weeks longer, I would be able to gather more data. Some days my time was really tight being busy with assignments and studies', 'If possible, I want 15 days more for this job because the friends I had invited weren't available during that rather short period' and 'I'd say one week has never been enough for me to get more data, especially when I had quizzes to prepare for'.

Apart from that, there were external factors that imposed constraints on the participants' ability to collect data. The majority agreed that the end of the year in southern

Thailand was not the time suitable for data collection, as shown in the statement, 'In this rainy season, it's hard for me to go outside by motorbike to collect data'. Additionally, many participants expressed their personal fear of using mobile phones when it was starting to rain. The quality of work affected by the weather conditions was also part of their concern, as in 'I think even taking photos during cloudy days wasn't a good idea'.

6. Discussion and conclusion

In this paper, we investigated the use of incentive mechanisms based on monetary and non-monetary approaches. We have assessed the impact of different motivating factors and designed strategies related to participants' performance of collecting and sharing data in a mobile safety crowdsourcing application. The study indicates the importance of how to design task-completed mechanisms in a way that would most engage people who may differ in their motivations.

The current study indicates that money is one crucial incentive in this task-based project, even if payments are relatively small. The payment-related incentives not only encourage people to actively participate in the project but also incentivized their good data collection behaviour and task quality, as found in this study. The participants with money incentives were found to set up the 'goals' to achieve in terms of the amount of money to earn in each day. However, a reduction of the participants' long-term intrinsic motivation that is evidenced should also be noted.

Among payment-related mechanisms, a fixed-price financial mechanism seems to be most appropriate for short period data collection with the aim of achieving data quality. Through referral incentives with proper designs, participant coverage tends to be largely extended, either spatially or temporally. It is also interesting to note that the low-price referral method became more motivating than the high-price referral one. One possible explanation for this may be participants' perceptions of task difficulties and possibilities to reach rewards. The participants in a high-price referral group may find it hard to complete more complicated tasks despite high payment offered to them. This perceived hard to reach rewards thus fail to encourage them to make sufficient effort to work on the tasks though their potential exists.

The non-monetary incentive mechanism seems to be motivating if it is compatible with socio-cultural values people are holding. The case of student participants in this study can be an example. These Thai students grew up in a collectivistic culture and had the characteristic of feeling indebted to the researcher who had been their former lecturer. They thus responded to a call for this study with no expectation of money in return. In this regard, it can be said that culture is a possible factor that determines incentive system success. This result could contribute to the strategic formulation of developing incentives mechanisms in other countries that have similar socio-cultural environments.

Future research recommendations include an experimental design conducted with a larger group of participants for the generalization of findings. It is also interesting to see whether individuals' demographic composition affect their decisions made on participating in tasks of different incentives and in what way incentives mechanisms impact upon their performance on tasks completion.

Notes

1. http://www.dell.com/.
2. https://www.threadless.com/.
3. http://www.istockphoto.com/.
4. https://www.innocentive.com/.
5. https://www.mturk.com.
6. https://microworkers.com/.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was funded by the Thailand Research Fund (TRF). This work is also supported by Department of Management Information Technology, Faculty of Commerce and Management, Prince of Songkla University on Trang campus, Thailand.

ORCID

Jurairat Phuttharak http://orcid.org/0000-0003-1785-4646

References

Anna, M. (2014). *A safetipin for our cities: Research findings of the study. Conducted in Thiruvananthapuram, Kerala 2014*. Thiruvananthapuram: Sakhi Women's Resource Centre. Retrieved from https://books.google.co.th/books?id=PMIOnQAACAAJ

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101.

Cebrian, M., Coviello, L., Vattani, A., & Voulgaris, P. (2012). *Finding red balloons with split contracts: Robustness to individuals' selfishness*. Proceedings of the Forty-fourth Annual ACM Symposium on Theory of Computing, pp. 775–788, New York, NY: ACM. doi:10.1145/2213977.2214047

Chatzimilioudis, G., Konstantinidis, A., Laoudias, C., & Zeinalipour-Yazti, D. (2012). Crowdsourcing with smartphones. *IEEE Internet Computing*, *16*(5), 36–44. doi:10.1109/MIC.2012.70

Deng, L., & Cox, L. P. (2009). *LiveCompare: Grocery bargain hunting through participatory sensing*. Proceedings of the 10th Workshop on Mobile Computing Systems and Applications, pp. 4:1–4:6. New York, NY: ACM; 2009. doi:10.1145/1514411.1514415

Doan, A., Ramakrishnan, R., & Halevy, A. Y. (2011). Crowdsourcing systems on the world-wide web. *Communications of the ACM*, *54*(4), 86–96. doi:10.1145/1924421.1924442

Douceur, J. R., & Moscibroda, T. (2007). Lottery trees: Motivational deployment of networked systems. ACM SIGCOMM Computer Communication Review, Vol. 37, pp. 121–132. ACM.

Franke, T., Lukowicz, P., & Blanke, U. (2015). Smart crowds in smart cities: Real life, city scale deployments of a smartphone based participatory crowd management platform. *Journal of Internet Services and Applications*, *6*(1), 1–19. doi:10.1186/s13174-015-0040-6

Goodchild, M. F., & Glennon, J. A. (2010). Crowdsourcing geographic information for disaster response: A research frontier. *International Journal of Digital Earth*, *3*(3), 231–241.

Guo, B., Chen, C., Zhang, D., Yu, Z., & Chin, A. (2016). Mobile crowd sensing and computing: When participatory sensing meets participatory social media. *IEEE Communications Magazine*, *54*(2), 131–137. doi:10.1109/MCOM.2016.7402272

Guo, H., Dai, G., Fan, J., Wu, Y., Shen, F., & Hu, Y. (2016). A mobile sensing system for urban monitoring with adaptive resolution. *Journal of Sensors*, *2016*, 1–15. doi:10.1155/2016/7901245

Hamilton, M., Salim, F., Cheng, E., & Choy, S. L. (2011). *Transafe: A crowdsourced mobile platform for crime and safety perception management.* 2011 IEEE International Symposium on Technology and Society (ISTAS), Chicago, IL, May, pp. 1–6.

Heer, J., & Bostock, M. (2010). *Crowdsourcing graphical perception: Using mechanical Turk to assess visualization design*. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, pp. 203–212. New York, NY: ACM. doi:10.1145/1753326.1753357

Jaimes, L. G., Vergara-Laurens, I. J., & Raij, A. (2015). A survey of incentive techniques for mobile crowd sensing. *IEEE Internet of Things Journal*, *2*(5), 370–380. doi:10. 1109/JIOT.2015.2409151

Kaufmann, N., Schulze, T., & Veit, D. (2011). *More than fun and money. Worker motivation in crowdsourcing – A study on mechanical Turk*. Americas Conference on Information Systems (AMCIS), 4–7 August, Detroit, Michigan.

Kleinberg, J., & Prabhakar, R. (2005). *Query incentive networks*. 46th Annual IEEE Symposium on Foundations of Computer Science (FOCS'05), pp. 132–141. doi:10.1109/SFCS.2005.63

Koutsopoulos, I. (2013). *Optimal incentive-driven design of participatory sensing systems*. Proceedings IEEE INFOCOM, pp. 1402–1410. doi:10.1109/INFCOM. 2013.6566934

Leesa-Nguansuk, S. (2018). *Thailand makes top 10 in social media use*. Retrieved from https://www.bangkokpost.com/tech/local-news/1420086/thailand-makes-top-10-in-social-media-use

Liu, N., & Chen, X. (2014). *Contribution-based incentive design for mobile crowdsourcing.* International Conference on Management of e-Commerce and e-Government (ICMeCG), pp. 151–155. doi:10.1109/ICMeCG.2014.39

Mason, W., & Watts, D. J. (2009). *Financial incentives and the performance of crowds*. Proceedings of the ACM SIGKDD Workshop on Human Computation, pp. 77–85. New York, NY: ACM. doi:10.1145/1600150.1600175

Mata, F., Torres-Ruiz, M., Guzmán, G., Quintero, R., Zagal-Flores, R., Moreno-Ibarra, M., & Loza, E. (2016). A mobile information system based on crowd-sensed and official crime data for finding safe routes: A case study of Mexico city. *Mobile Information Systems*, *2016*, 1–11. doi:10.1155/2016/8068209

Morschheuser, B., Hamari, J., & Koivisto, J. (2016). Gamification in crowdsourcing: A review. IEEE 2016 49th Hawaii International Conference on System Sciences (HICSS), Koloa, HI, pp. 4375–4384.

Murphy, E., & King, E. A. (2016). Smartphone-based noise mapping: Integrating sound level meter app data into the strategic noise mapping process. *Science of The Total Environment*, *562*, 852–859. doi:10.1016/j.scitotenv.2016.04.076

Naik, N., Philipoom, J., Raskar, R., & Hidalgo, C. (2014). Streetscore – predicting the perceived safety of one million streetscapes. Proceedings of the 2014 IEEE Conference on Computer Vision and Pattern Recognition Workshops, pp. 793–799. Washington, DC: IEEE Computer Society. doi:10.1109/CVPRW.2014.121

Naito, K., Tani, S., & Takai, D. (2016). Implementation of mobile sensing platform with a tree based sensor network. In G. Pietro, L. Gallo, R. Howlett, & L. Jain (Eds.), *Intelligent interactive multimedia systems and services 2016. Smart innovation, systems and technologies* (Vol. 55, pp. 213–225). Cham: Springer.

Naroditskiy, V., Rahwan, I., Cebrian, M., & Jennings, N. R. (2012). Verification in referral-based crowdsourcing. *PloS One*, *7*(10), e45924.

Naroditskiy, V., Stein, S., Tonin, M., Tran-Thanh, L., Vlassopoulos, M., & Jennings, N. R. (2014, November 2–4). *Referral incentives in crowdfunding*. HCOMP2014: Conference on Human Computation & Crowdsourcing, pp. 171–183.

Oomen, J., & Aroyo, L. (2011). *Crowdsourcing in the cultural heritage domain: Opportunities and challenges*. Paper presented at the proceedings of the 5th International Conference on Communities and Technologies, Brisbane, Australia.

Ordonez, V., & Berg, T. L. (2014). *Learning high-level judgments of urban perception*. doi:10.1007/978-3-319-10599-4_32

Porzi, L., Bul, S. R., Lepri, B., & Ricci, E. (2015). *Predicting and understanding urban perception with convolutional neural networks*. Paper presented at the proceedings of the 23rd ACM International Conference on Multimedia, Brisbane, Australia.

Quinn, A. J., & Bederson, B. B. (2011). *Human computation: A survey and taxonomy of a growing field*. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, pp. 1403–1412. New York, NY: ACM. doi:10.1145/1978942. 1979148

Reddy, S., Estrin, D., Hansen, M., & Srivastava, M. (2010). *Examining micro-payments for participatory sensing data collections*. Proceedings of the 12th ACM International Conference on Ubiquitous Computing, pp. 33–36. New York, NY: ACM. doi:10.1145/1864349.1864355

Swan, M. (2012). Crowdsourced health research studies: An important emerging complement to clinical trials in the public health research ecosystem. *Journal of Medical Internet Research*, *14*(2), e46. doi:10.2196/jmir.1988

Vergara-Laurens, I. J., & Labrador, M. A. (2013). *Preserving privacy while reducing power consumption and information loss in LBS and participatory sensing applications*. 2011 IEEE GLOBECOM Workshops (GC Wkshps), pp. 1247–1252. doi:10.1109/GLOCOMW.2011.6162381

Vergara-Laurens, I. J., Mendez-Chaves, D., & Labrador, M. A. (2013). *On the interactions between privacy-preserving, incentive, and inference mechanisms in participatory sensing systems*. doi:10.1007/978-3-642-38631-2_47

Wang, X., Zheng, X., Zhang, Q., Wang, T., & Shen, D. (2016). Crowdsourcing in ITS: The state of the work and the networking. *IEEE Transactions on Intelligent Transportation Systems*, *17*(6), 1596–1605. doi:10.1109/TITS.2015.2513086

Yan, T., Hoh, B., Ganesan, D., Tracton, K., Iwuchukwu, T., & Lee, J. (2011). *CrowdPark: A crowdsourcing-based parking reservation system for mobile phones*. University of Massachusetts at Amherst Tech Report.

Yang, D., Xue, G., Fang, X., & Tang, J. (2012). *Crowdsourcing to smartphones: Incentive mechanism design for mobile phone sensing*. Proceedings of the 18th Annual International Conference on Mobile Computing and Networking, pp. 173–184. New York, NY: ACM. doi:10.1145/2348543.2348567

Yerva, S. R., Jeung, H., & Aberer, K. (2012). *Cloud based social and sensor data fusion*. 15th International Conference on Information Fusion, Singapore, pp. 2494–2501.

Yuen, M. C., Chen, L. J., & King, I. (2009). *A survey of human computation systems*. International Conference on Computational Science and Engineering, 2009 (CSE '09), Vol. 4, pp. 723–728. doi:10.1109/CSE.2009.395

Yuen, M. C., King, I., & Leung, K. S. (2011). *A survey of crowdsourcing systems*. 2011 IEEE Third International Conference on Privacy, Security, Risk and Trust and 2011 IEEE Third International Conference on Social Computing, Boston, MA, pp. 766–773. doi:10.1109/PASSAT/SocialCom.2011.203

Zheng, X., Chen, W., Wang, P., Shen, D., Chen, S., Wang, X., … Yang, L. (2016). Big data for social transportation. *IEEE Transactions on Intelligent Transportation Systems*, *17*(3), 620–630. doi:10.1109/TITS. 2015.2480157