

PARTICIPATORY SENSING: DEMOGRAPHIC DETERMINANTS OF
INCENTIVE EFFECTIVENESS AND A FRAMEWORK FOR ESTABLISHING
INCENTIVE DESIGN GUIDELINES

by

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ABSTRACT

OSARIE ME OMOKARO. participatory sensing: demographic determinants of incentive effectiveness and a framework for establishing incentive design guidelines.
(Under the direction of DR. JAMIE PAYTON)

Participatory sensing, in which volunteers use the sensors on their smartphones to capture and transmit digital samples of the surrounding environment, shows promise for large-scale data collection. Recently, researchers have begun to explore the use of incentives to motivate participation in these kinds of data collection campaigns. This study investigates the influence of demographics on the effectiveness of incentives to motivate volunteer data collection in participatory sensing. The hypothesis that age, sex, ethnicity and education have an influence on the effectiveness of incentives to promote volunteer participation in a data collection campaign was evaluated via a large-scale survey of 260 respondents. Findings showed that the demographic of age had an influence on social motivation. These findings were validated in a real-world participatory sensing context, using two user studies. The user studies were conducted using participatory sensing applications developed and deployed in two different domains. The two user studies (a) Foodie Frenzy and (b) Watch it Bloom measured motivation and engagement via a pre-survey and a post survey respectively. Findings from both studies were used in the evaluation of a framework designed to provide a generalized reusable solution for the selection of incentives in the participatory sensing domain. The implication of this research is its potential to close the gap in the process of developing and selecting targeted incentives to motivate and encourage sustained volunteer participation in the field of participatory sensing.

DEDICATION

Dedicated to the memory of Prof. Dave Nosa Omokaro, my late father who sacrificed all to make sure I had the best education. Your unreserved love during your life time built my confidence to achieve my dream. Your legacy lives on.

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CHAPTER 1: INTRODUCTION

Participatory sensing, in which volunteers use the sensors on their smart phones to capture and transmit digital samples of the surrounding environment, shows promise for large-scale data collection. The pervasive adoption of phones enables the participatory sensing approach to support large-scale volunteer data collection that allows an investigator to identify patterns across a wider geographical reach than with traditional special-purpose environmental sensors. Such an approach can be used to supplement data collected by special-purpose sensors or even replace their use, providing data from a fine-grained, human perspective and potentially reducing the costs associated with large-scale data collection. A number of participatory sensing applications have been developed for a variety of domains, including environmental monitoring [38, 40, 28], wildlife and habitat monitoring [37, 44], health and well-being [52, 15, 26], social networking [39], road traffic monitoring [62], and fuel-efficient driving [17]. In such campaigns, participatory sensing applications installed on volunteers' mobile phones enable them to capture data enriched with contextual information (e.g., location, time, situation) about themselves or their environments, through the use of the sensors embedded in their commercial smart phones (e.g. microphone, camera, GPS, and accelerometer etc). To provide a deeper understanding of the concept of participatory sensing, its advantages and challenges, we consider a case of oil spills in the Niger Delta region of Nigeria, where this approach could

potentially provide a remedy for the growing trend of violence and youth restiveness in the region by promoting accountability and fostering dialogue among communities, oil companies, and government agencies.

1.1 The Case of Oil Spills in the Niger Delta, Nigeria

Oil exploration has been on-going in Nigeria for over 50 years [20]. With a large number of oilfields, the Niger delta supplies 40% of the crude imported by the United States [66]. However, due to decades of oil production, the Niger Delta is considered by environmentalists as one of the most polluted regions in the world. The region is faced with incessant oil spills caused by oil companies taking advantage of the opportunities to drill and lay pipelines, which are often run through villages and farmlands. Oils spills occur due to leakage from rusty pipelines and also from vandalism, theft or sabotage by restive youth in the communities due to the perceived injustice, marginalization, and selfishness of oil companies and the government. These oil spills cause pollution which have a direct impact on the health and livelihood of villagers– mainly farming and fishing.

Identifying leaks would require constant monitoring of pipelines using dedicated sensors, which are costly to install. Furthermore, the current process of reporting spills is cumbersome, involving bottlenecks and dedicated government agencies that may not have the community’s interest at heart. This is according to a recent UN report that the process of investigation, reporting and clean-up of spills is deeply flawed in favor of the firms and against the victims [66].

To solve this problem, participatory sensing could be used as a potential solution

to identify and report the leaks immediately as they occur so they can be repaired more quickly to reduce damages, foster a sense of citizen responsibility and corporate responsibility towards reducing pollution. The goal of lower pollution could potentially be used to unite citizens and corporations in a mutual interest. The community could be engaged as volunteers who use their phones to collectively identify high areas of pollution, log pollution information, and take steps to reduce it. A technology system comprising mobile phones, a data collection application, and a web based platform could be deployed. Individual volunteers could download the app and use the visual sensors on their mobile phones to capture images or videos of pollution as it occurs. The automatically geo-tagged and time-stamped images will be uploaded to the web-based platform where the data will be analyzed and displayed. This would likely increase accountability of the oil companies and create a sense of empowerment for the affected communities.

The use of participatory sensing in this context poses a few challenges. Given the fact that oil spills occur both in remote villages, where the population is mostly elderly and illiterate, and also in cities, which feature a more vibrant and youthful population, what incentives should be used? Will the incentive provided apply to both demographic groups? And if not, what specific incentives are more effective for each demographic group or the campaign as a whole?

1.2 Background and Related Work

This section presents a description of crowd-driven problem-solving activities (including participatory sensing) and identifies theories of motivation that we can draw

from as a foundation for this project. The growing prevalence of mobile devices such as smart phones and tablet PCs, coupled with the willingness of citizens to volunteer data, has brought rise to the establishment of participatory sensing as a field of research. Participatory sensing, in which volunteers use the sensors on their smart phones to capture and transmit digital samples of the surrounding environment, shows promise for large-scale data collection. The pervasive adoption of phones enables the participatory sensing approach to support large-scale volunteer data collection that allows an investigator to identify patterns across a wider geographical reach than with traditional special-purpose environmental sensors. Such an approach can be used to supplement data collected by special-purpose sensors or even replace their use, providing data from a fine-grained, human perspective and potentially reducing the costs associated with large-scale data collection. Participatory sensing, however, is not an entirely new concept; instead, it can attribute its roots to citizen science and crowdsourcing.

1.2.1 Citizen Science

Up until around the 1950s, citizens relied on scientists, public officials and administrators to make decisions about a variety of issues ranging from personal matters such as health, diet, child care, and employment, to leisure and protests [24]. The latter part of the 20th century saw a shift toward greater citizen involvement and citizen participation in the decisions that affect their lives [54]. Given the fact that citizens had more intimate knowledge of patterns and anomalies in their environment and communities [22], the need for them to be empowered to respond to these anomalies

and patterns was imperative [54]. This ideology spawned citizen science, a form of research where citizens act as these informal data collectors to help scientists track and study problems in their field of research. In its truest form, citizen science is a distributed data collection method performed by volunteers aggregated across space and time, and often focused on scientific and educational goals. Examples of Citizen Science projects include the United States Environmental Protection Agency’s (EPA) Volunteer Monitoring and Assessing Water Quality Program [64]. The EPA builds connections between national scientific agencies and local citizens. In this program, the EPA trains citizen volunteers to perform specific tasks, including screening for water quality problems and measuring baseline conditions and trends in their local communities. The volunteers report their findings to EPA scientific bodies, who then analyze the data and use the results to make policy recommendations to local, state, and federal legislative authorities. Other successful applications of citizen science include the National Audubon Society’s Christmas Bird count [42].

1.2.2 Crowdsourcing

The term crowdsourcing, coined by Jeff Howe and Mark Robinson, describes an online model that harnesses the creative solutions of a distributed network of individuals (the “crowd”) as sources for processing large sets of data and completing small tasks in order to solve large, complex problems. This can take the form of peer-production, when the job is performed collaboratively or undertaken by sole individuals [21]. By its very nature, crowdsourcing relies on its users, as well as online technology, to perform the tasks at hand. An example of crowdsourcing is an online platform called

Amazon Mechanical Turk system [3], developed by Amazon.com. Amazon Mechanical Turk can be utilized as an online labor market, where users log into the system to complete Human Intelligence Tasks (or HITs). These are specific, defined micro tasks that require a level of human intelligence and cognition to complete [61]. Completing a HIT could involve providing answers to simple, discrete questions. These questions are generated by the scientist (or whomever has a question), the scientists pay a small fee to the user for each answer they provide. Other examples of crowdsourcing include further efforts to use human intelligence to perform small tasks that lead to solving a larger-scale problem. For example, ReCAPTCHA leverages the intelligence of the crowd for human verification, in order to create complete digitized documents. ReCAPTCHA provides a free service that helps digitize books and newspapers. Book pages are scanned using “Optical Character Recognition” (OCR) and transformed into text [67]. Words that cannot be deciphered by the OCR are placed on an image and converted into CAPTCHA, which is then placed on websites to avoid spam. When a user visits a website, the CAPTCHA is presented to the user with two words, one which is computer generated and has a known answer, and another which is a scan of an unknown word. The program assumes that a user’s answer to the unknown word is correct, if the user answers correctly to the known word.

1.2.3 Collective Intelligence

More recently, new forms of crowdsourcing enabled through the power of the web have emerged. These include online platforms such as Wikipedia, Threadless and Innocentive, and are commonly referred to as collective intelligence communities. These

new crowdsourcing models shift away from the “defined microtask” mechanisms employed by AMT and ReCAPTCHA to deriving value through the collaborative efforts of the crowd. For example, Innocentive, a global web-based community, connects top research and scientific organizations to external brainpower that can provide ideas and solutions to their toughest research challenges [21, 2]. The client companies, called “seekers” work with Inncoentive to define their problems; the problems are posted on Innocentive’s website and the “solver’s,” individuals who have the expertise, provide the solutions. The solution that best fits the criteria of the “seeker’s” receives a reward. Other forms of collective intelligence involve performing tasks that require specific skill sets such as web design, photography, writing/editing and fashion design to solve problems.

1.2.4 Participatory Sensing

In 2006, UCLA’s Center for Embedded Networked Sensors (CENS) [63] and Center for Research in Engineering, Media and Performance (REMAP), began research on a new field called Urban Sensing Systems. Their fundamental goal was to use embedded, mobile technologies to enhance daily human existence and civility in the society, and stir up public perception through technology-driven cultural channels. Also pivotal was harnessing the potential benefits of the already existent and prevalent user interactions with mobile technologies in the sensing process. This became the foundation of a new idea called participatory sensing, which leverages the mobile phones carried by over 4.6 billion people around the world [6]. Most modern mobile devices include a number of relatively simple sensors that can be useful in capturing

observations for participatory sensing campaigns, including microphones, cameras, accelerometers, shake sensors, GPS receivers, barometers, and other specialized sensors. The combination of such simple sensors could be used by volunteers to perform simple tasks that generate data, which could be used to make inferences about complex phenomena in the environment. This presents a unique opportunity that extends the mechanisms from both Citizen Science and Crowdsourcing. The main advantage of participatory sensing is the ability to collect data across huge geographic areas by utilizing volunteers and their mobile devices, thus expanding the scientists' reach across multiple domains. Gathering observations from multiple independent sources allows large data sets to be analyzed and categorized from different perspectives [48].

1.3 Characteristics of Participatory Sensing Applications

Participatory sensing applications vary in terms of the purpose of data collection and differ in how involved participants are in the sampling process for data collection [53]. A number of participatory sensing applications have been developed for a variety of domains, including environmental monitoring, wildlife and habitat monitoring, health and well-being, shopping and commerce as well as social networking [39], road traffic monitoring [62], and fuel-efficient driving [17]. In such campaigns, participatory sensing applications installed on volunteers' mobile phones enable them to capture data enriched with contextual information (e.g., location, time, situation) about themselves or their environments, through the use of the sensors embedded in their commercial smart phones (e.g. microphone, camera, GPS, and accelerometer etc).

1.3.1 Environmental Monitoring

In environmental monitoring, applications are developed to enable users to monitor their exposure to environmental pollutants such as air, water and noise. This information provides support for decisions about how users impact their environment, and how their environment impacts the user. One common example of an environmental monitoring application is the Personal Environmental Impact Report (PEIR) [40]. The PEIR application uses the GPS sensor or a history of cellular tower handoffs to construct a trace of the participant's movements over time. The PEIR application server reconciles the participant's location information with environmental data and scientific data models to give the user feedback about their exposure to harmful chemicals and their personal impact on the environment. This application requires repeated sampling of data by the participant in order to provide accurate exposure information based on the user's location. Other environmental monitoring applications include, Mendez et al, Reddy et al and Kim et al [38, 40, 28].

1.3.2 Wildlife and Habitat Monitoring

Wildlife and habitat monitoring applications are developed to engage communities in the early detection, prevention and awareness of plants and species in the environment. For example, Project Budburst [43] highlights this with its national effort to collect phenological events within nature to track and predict climate change. Participants track particular plants to observe the seasonal changes that plant undergoes (first bloom, leaves changing colors, etc.). By taking pictures of the phenological events, the scientists are able to create a database of the spatial and temporal charac-

teristics of the entire country, which they in turn show to the users using an overlay onto a map. This type of data collection would be much more difficult without the use of volunteers to submit data, and technology to make observations about the environment. Other applications in this category include [37, 44]. These types of applications typically require participants to go to certain locations at certain times in order to provide relevant data.

1.3.3 Health and Well-being

The rising costs of healthcare have resulted in growing interest in participatory sensing applications that are intended to engage users in self-monitoring of activities and behaviors, with the goal of encouraging activities that have a positive impact on health and well-being. In many of these applications, participants are provided with the ability to monitor and visualize information about their personal health choices and exercise habits, and require day to day input from the user to provide accurate and relevant feedback. For example, BikeNet [15] uses mobile phones and integrated static sensors mounted on a bicycle to collect data about the cycling milestones (speed, distance, etc.), and provides participants with experience maps of their biking activities. DietSense [52] is a participatory sensing application in which participants are given a mobile phone that automatically captures images and audio clips every 10-15 seconds as participants go about their daily activities. These images and audio clips are then reviewed by the participant and relevant data are selected and uploaded to healthcare professionals, who then use the data to perform their own research regarding dietary intake. Other health and well being application include,

[52, 15, 26].

Shopping and Commerce

Participatory sensing has also been leveraged for shopping and commerce to help consumers to be informed about prices of goods and services. For example, participants are asked to go to stores and take photos of price tags along with bar codes to aid shoppers in finding the best deals at grocery stores, using LiveCompare [13]. In return for sharing a photo of a product, participants are provided with a listing of prices for the product within the local area. The goal of LiveCompare is to provide pricing information to promote fair trade, competition, and historical data concerning their pricing structures. Mobishop [58] has similar goals, but asks participants to provide photos of shopping receipts, which are tagged with location information.

1.4 Participatory Sensing vs Crowdsourcing and Collective Intelligence

The reliance on human intelligence and volunteers to provide better insight into the environment and everyday problems provides great similarities between participatory sensing, crowd sourcing, and collective intelligence. Conversely, there are differences in the platform and user interaction styles for participatory sensing and the other platforms. The wide variety of participatory sensing applications require different kinds of user interactions. Some applications require only passive interactions from the participants, while others require active participation. For example, in BikeNet and PIER, a volunteer can autonomously allow the sensors on their mobile phones to monitor and upload their activity level or exposure to pollution over time. While in applications like Live Compare and DietSense, volunteers have to actively go to

a grocery store to take photos of price tags or repeatedly take photos of their food. Participatory sensing also places spatio-temporal constraints on the volunteer. In applications like Project Noah and Project Budburst, volunteers may have to go to certain locations at certain times of the year to capture images of animals and plants. This involves repeated participation over time to track seasonal changes such as first bloom and leaves changing colors.

In contrast, crowdsourcing and collective intelligence are typically performed on on-line platforms, which remove the hardware constraints and data plan costs associated with participatory sensing applications. For example, to complete a HIT on AMT, a “requester” may be asked to view an image and describe it, fill out a survey or write a product review. These are quick, simple one time tasks done over the internet with no hardware or spatio-temporal constraints attached. Participants using these platforms can log in to participate using a dedicated computer that is connected a power source and internet. This makes it convenient for people already doing other tasks to participate.

1.5 Participatory Sensing Challenges

One challenge for participatory sensing is that the quantity and quality of data provided to the campaign is largely dependent on volunteers who must expend their own resources (e.g., battery consumption and data plan usage on mobile phones) to collect data. This may result in a lack of user motivation to participate in a campaign over time [57]. Furthermore, participatory sensing relies on the recruitment of volunteers from an undefined and generally large body of people who are anything

but a homogeneous group. Volunteers are diverse in terms of demographics (gender, age, ethnicity and educational background), yet incentives in participatory sensing continue to be applied in a one-size-fits-all manner. There is a lack of information on what types of incentives appeal to different demographic groups of users.

The use of incentives to motivate volunteers to utilize their resources and engage in capturing and transmitting data in any kind of data collection campaign has been explored by researchers. However, much of the research on motivation for applications that rely on volunteers has not been explicitly studied in the context of participatory sensing. Instead, much of the research focuses on crowdsourcing and collective intelligence communities [61]. Although the findings in these domains are relevant given the similarities in the use of volunteers, understanding motivation and the use of incentives in participatory sensing is much more relevant given that a volunteer could be required to be present at a particular location at a given time and their participation is expected to be repeated over time.

1.6 Research Statement

1.6.1 Statement of Problem

Lack of knowledge on the demographic factors that influence volunteers to perceive and respond to incentives, impairs to a great extent the ability of application designers to identify what satisfies the requirements of different campaigns. This lack of knowledge also impairs the ability to implement incentives that meet large scale data quantity and quality needs. Furthermore, the absence of a framework for identification of variables that influence the effectiveness of incentives poses a challenge to

designing result oriented sensing applications. This inadequacy has created gaps in the process of developing targeted approaches to encourage sustained participation.

1.6.2 Thesis Objective

This study investigated demographic determinants of user motivation and engagement in participatory sensing. Its specific objectives were to identify non-monetary incentives and the influence of age, sex, ethnicity and education on their effectiveness as promoters of individual participation. A framework for establishing design guidelines for participatory sensing incentives was developed to enable developers to create targeted incentive mechanisms to motivate volunteer contributions.

The following were the specific objectives of this study:

1. To determine if the effectiveness of an incentive in participatory sensing varies by demographics
 - To determine if the *age* of a volunteer has any significant influence on effectiveness of incentive (ages: Under 30 and 30+)
 - To determine if the *sex* of a volunteer is a factor influencing effectiveness of incentive (sex: Male and Female)
 - To determine if the *ethnicity* of a volunteer is a factor influencing effectiveness of incentive (ethnicity: White, Black and Others)
 - To assess if the *education* of a volunteer has significant influence on effectiveness (education: College and below, Graduate School)
2. To develop and evaluate a framework for providing generalized reusable incen-

tive solutions in participatory sensing

3. To provide incentive design guidelines for participatory sensing in the Niger Delta, Nigeria

1.6.3 Thesis Significance

This study provided empirical data on the demographics of volunteers and their influence on the effectiveness of incentives in participatory sensing. Such data will inform designers of participatory sensing applications to adopt targeted approaches to creating and selecting incentives that encourage large scale participation and high quality data submissions. The developed framework serves as a building block for designing generalized reusable incentive solutions that can be tailored for a variety of applications and associated collections of users. In particular, this work addressed the following questions:

- Do demographics influence the effectiveness of non-monetary incentives in participatory sensing applications?
- How can incentives be tailored to motivate and increase user engagement in participatory sensing applications?
- How can support be provided for campaign organizers to select effective incentives for their particular groups of users and application domains?

1.7 Definition of Terms

For the purpose of this study, the following terms were operationally defined as given below:

- Effectiveness of incentive: An incentive is effective if it increases a volunteer’s willingness to provide data to a campaign. This is indicated by the quantity and quality of contributions made to a campaign.
- Engagement: Engagement is indicated by a volunteer’s continued participation for the duration of the campaign.
- Demographics: age, sex, ethnicity and education of a volunteer

1.8 Organization

In Chapter 2, existing literature is reviewed to lay the foundation for this work. This chapter highlights the need for the consideration of demographic differences and how these factors influence a volunteer’s willingness to provide data to a campaign. The chapter also highlights the lack of research on the use of non-monetary incentives in the participatory sensing domain. Chapter 3 addresses the survey conducted to investigate the influence of demographics on the effectiveness of non-monetary incentives in participatory sensing. Chapter 4 introduces a framework—4WT—developed to provide a generalized reusable solution for incentive selection in participatory sensing. Chapter 5 presents two user studies conducted to validate the survey findings in a real-world participatory sensing context and to show transfer of findings to a different domain. Chapter 6 evaluates the applicability of the 4WT framework for the selection of incentives in participatory sensing. Lastly, Chapter 7 presents a summary and conclusion of this work.

CHAPTER 2: LITERATURE REVIEW

This section presents a range of theories in motivation and engagement in an attempt to shape an understanding of a set of interrelated concepts which lay the foundation for this work. We draw from traditional behavior theories and models that describe motivation and behavior change in individuals. In addition to these theories, much focus is on motivational models that are specifically designed for the use of mobile technologies to persuade and motivate target user behaviors. In this regard, the following theoretical perspectives and models are reviewed; The Herzberg Two-Factor Motivation Theory, Theory of Planned Behavior (TPB), Theory of Burnout and Engagement, and Foggs Behavior Model. These theories will be revisited in further chapters to provide clarity and motivation for parts of this work.

2.1 Theories of Motivation and Engagement

2.1.1 Herzberg Two-Factor Motivational Theory

Deci et al in the Herzberg Two-Factor Motivational Theory [12] defined motivation as being energized, moved to, or inspired to do something. This work differentiates between intrinsic and extrinsic motivation, stating that intrinsic motivation involves doing an activity simply because of interest, enjoyment or the inherent satisfaction of performing the activity itself. While extrinsic motivation involves doing an activity in order to attain some external outcome that may involve personal ego (approval

from self or others) or rewards. For example, a student could be motivated to do homework out of curiosity; another may be motivated to get a parent or teacher's approval, while another student may be motivated by the challenge.

2.1.2 Theory of Planned Behavior

Theory of Planned behavior (TPB) [1] proposes that an individual's behavior in any given situation is determined by the individual's attitude towards the behavior, the measure of their own competence to complete the task, and social attitudes/environmental factors such as the perceived consequence and implication of performing the task. According to TPB, a person's attitude towards a behavior is defined by an overall evaluation of the behavior; this involves beliefs about the consequences of performing the behavior and the corresponding positive or negative judgments towards the behavior.

2.1.3 The Theory of Burnout and Engagement

Engagement [35] is defined as a positive, work-related state of well-being, characterized by energy, involvement, self-efficacy and an effective connection with one's work. Although researchers Schaufeli and Bakker[57] have a similar definition of engagement as "a positive, fulfilling, work-related state of mind", their work characterizes engagement differently, as vigor, dedication and absorption with the work performed. Dedication is described as being strongly involved in one's work, experiencing a sense of significance, enthusiasm, inspiration, pride, and challenge. While absorption is characterized by being happily engrossed in one's work. On the other hand, burnout is indicated by lower motivation and lower efficacy.

Each of these theories provide insight into the Who, Why, What, Where and When of motivating individuals to provide data to participatory sensing campaigns. Insights from these theories are used in of the 4WT framework described in chapter 4.

2.2 Persuasive Technology Models

Recently, there has been an increase in the body of work that examines individual motivation specifically for technology use. Of these models, the Technology Acceptance Model and the Foggs Behavior Model are reviewed. These two models have been successfully applied to technology use in various domain and represent the most cited models in persuasive technology literature. A brief description of the models are provided here, however these models, particularly the Foggs Behavior Model, will be revisited in further sections.

2.2.1 Technology Acceptance Model

The Technology Acceptance Model (TAM) [65] is widely accepted as a framework to understand users' technology acceptance processes and has been used across a wide variety of contexts. TAM states that an individual's intention to adopt a technology predicts the individual's actual usage of the technology. Intention to adopt technology is explained by two major perceptual factors: perceived ease of use and perceived usefulness. Perceived usefulness is in turn, influenced by perceived ease of use.

2.2.2 Foggs Behavior Model

Fogg's model defines core motivators as social acceptance or rejection, pleasure or pain, and hope or fear. Social acceptance is defined as the desire to belong to a stable framework of some ongoing relationship in which individuals share a mutual concern,

while social rejection is a negative state in which individuals do not receive the benefits of inclusion [14]. The pleasure/pain motivator is related to emotional pleasure or pain and the effect on attitudes, intentions, values or personal norms [11], and is characterized by responses to feelings or circumstances happening in the moment. Hope is the anticipation of something good happening, while fear is the anticipation of something bad, often the anticipation of loss [29].

2.3 Motivating Volunteer Data Collection Activities

Research has been conducted to understand the use of different types of incentives for motivating volunteer data collection behaviors in crowdsourcing, collective intelligence and participatory sensing systems. An overview of some of the relevant studies is provided in the following sections.

2.3.1 Motivation in Crowdsourcing and Collective Intelligence

Rashid et al. demonstrate that within a recommendation system, showing users the value of their contribution positively impacts motivation and work provided by that user. This research demonstrates that a participant's understanding of their identity in the community, and their ability to reflect on their impact can act as motivational factors [50]. Shaw et al [59] measured the effectiveness of 14 different incentives for a task in an online context. They found that social incentives have no significant effect on performance in this context, while incentives such as financial-punishment increased engagement with the task and thus produced better performance. Similarly, a survey was conducted to understand different motivations and participation styles in online collective intelligence environments. The survey involved people par-

ticipating in Amazon Mechanical Turk (AMT) and Wikipedia, and results showed that reward was a relevant motivator to participate in AMT, but had little relevance in Wikipedia [32]. The incentives had different effects in different environments. Additionally, an assessment of motivation on task performance in crowdsourcing found that factors which increase the intrinsic motivation of a task (e.g., framing a task as helping others) succeeded in improving output quality, while extrinsic motivators such as increased pay did not [55].

2.3.2 Motivation in Participatory Sensing

In participatory sensing, researchers aim at motivating volunteers to provide the desired quantity and quality of data samples required by a campaign organizer by offering something volunteers want or need as an incentive. Incentives typically fall into two categories, monetary and non-monetary.

2.3.2.1 Monetary Incentives

To date, participatory sensing has largely relied on monetary incentives to encourage participation. The use of micropayments, in which small tasks are matched with small payments for each data submission to a campaign, was introduced by Reddy et al [51]. The authors found that this type of monetary incentive helped to increase interest in participating and reinforced good data collection habits, but were more beneficial when combined with other motivating factors, e.g., within the context of competitive activities. While this approach can encourage participation, it is difficult for a campaign organizer to select an optimal fixed price, and a user's perceived value of his data contributions may change over time. Lee and Hoh [31] address the draw-

back of the previous approach by setting a dynamic price. The problem of balancing minimal incentive cost with maximizing user participation is addressed by introducing the Reverse Auction based Dynamic Price (RADP) incentive mechanism. In RADP, users sell their sensing data to campaign organizers with a bid price. Data providers define a price (bid) for their data and the participatory sensing campaign organizer selects the k lowest bids. The selected users receive their bid prices as a reward for their sensing data. The incentive mechanism focuses on minimizing and stabilizing incentive cost while maintaining an adequate number of volunteers by preventing users from dropping out of participatory sensing applications. Lee achieves a 60% incentive cost reduction compared with previous methods, while reducing participant drop outs and maintaining competitive bid prices.

Although widely used, studies show that monetary incentives may not always be effective for motivating and engaging participation. Research by Mason and Watts [36] shows that financial incentives increase quantity but not the quality of work performed by participants. Further studies by Gneezy et al [18] found that participants who were offered monetary incentives performed more poorly than those who were offered no compensation. Gneezy also suggests that paying significant amounts for user data is contradictory to most campaigns, as the goal of participatory sensing is often to collect large data sets for a minimal investment. Also, non-monetary incentives are perceived to be more valuable than cash incentives because they provide satisfaction which comes from knowledge of doing good rather than the reward itself [23].

2.3.2.2 Non-Monetary Incentives

Some participatory sensing applications such as Green GPS [17], Ubifit Garden [9] and Cence Me [39] have explored the use of non-monetary incentives such as personal gain, gamification and social networks to encourage and sustain volunteer participation. However, these types of non-monetary incentives have been applied largely as ad hoc approaches and have yet to gain traction in the participatory sensing community. This gap in research surrounding non-monetary incentives and their applications in participatory sensing, drives the need for an explicit study and categorization of these types of incentives. To close this gap, non-monetary incentives are identified and a taxonomy identifying how they relate to the core motivational categories of the Fogg's Behavior Model is developed.

2.3.2.3 Closing the Gap: Non-Monetary Incentives in Participatory Sensing

Although there are many ways to classify the spectrum of influences that motivate individuals [32], B.J Fogg's Behavioral Model for Persuasive Design (FBM) [16] described in section 2.2.2 is used. B.J Fogg studies the design and use of persuasive mobile technology systems such as mobile phones to impact and encourage target user behavior. FBM has since become widely considered to be the foundation for motivation using persuasive technologies, as the number of publications that cite this work in the field has increased steadily. As described in section 2.2.2, Fogg's model defines core motivators as social acceptance or rejection, pleasure or pain, and hope or fear. This model has been applied to various domains including, human-computer interaction, to help HCI researchers understand how to develop interaction techniques

that motivate users to use the system in a particular way, e-learning [41], and selection of guidelines for technology systems [11]. FBM is particularly relevant to the study of non-monetary incentives in participatory sensing because unlike other motivational models discussed, FBM applies most directly to practical issues of creating behavior change involving the use of mobile technology [16].

Although successful, a limitation of FBM is that it provides no guidance on how to appeal to these motivational categories. For example, if an individual is known to be motivated by social acceptance, how can a campaign organizer appeal to this motivation using incentives? To address this limitation, non-monetary incentives for participatory sensing are classified under the three core motivators in FBM. This classification provides a frame of reference for campaign organizers to consider various motivational categories and the use of non-monetary incentives as a mechanism to target such motivation.

- **Social acceptance and rejection:** Researchers have developed incentives based around the desire for social acceptance; these types of incentives appeal to the desire to have a shared experience with one or more individuals [32] or to be recognized within a community of peers. For example, social interaction may include working as part of a team or the ability to share contributions with friends and family via social networks [39], while social recognition [23] may take the form of public acknowledgment of specific activities, trophies for reaching certain levels of accomplishments, reinforcement through messages provided by friends in social networks or simply being identified with a cause or community.

- Pleasure and pain: Csikszentmihalyi [10] describes this sensation as being *autotelic*: needing few material possessions, little entertainment, comfort, power, or fame because so much of what the individual does is rewarding in itself. Autotelic incentives are characterized by curiosity, the desire to learn, and sheer enjoyment of performing the activity. In a participatory sensing application, a participant may be interested in a campaign that relates to a personally held belief or moral concern; this would be considered an autotelic incentive. For example, an animal lover would be inclined to participate in a campaign that helps to report abuse of animals. Others may be motivated by what is perceived as an obligation or responsibility to help their community, or motivated to avoid the feeling of guilt for not being responsible; a person may feel good for reporting suspicious activity in their neighborhood, knowing that they are helping to protect others, or may feel guilty for a negative occurrence in the neighborhood that they could have reported.
- Hope and fear: Incentives such as monetary gain and rewards have been successful in motivating data collection in participatory sensing campaigns because of the anticipation of receiving rewards or the fear of losing them when providing very few or low-quality data contributions. The LiveCompare participatory sensing application, for example, employs the use of discounts at major vendors for contributions of data about product prices [13]. Other incentives that provide a challenge (e.g., game-like incentives with leader boards, missions, and scoring) [19] also fall under this category.

2.4 Influence of Demographics on Motivation

Research in motivation has shown that individuals vary not only in their degree of motivation but also in the type of motivation (nature and focus) that gives rise to actions [12]. Different types of users can have vastly different reasons for participating [8], and incentives for motivating volunteer data collection behaviors do not have the same effect for different demographic groups of volunteers. This is evident in studies on the influence of volunteer responsiveness to incentives conducted mostly in crowdsourcing and collective intelligence domains.

2.4.1 Crowdsourcing and Collective Intelligence

A study on Galaxy Zoo [49], an online astronomy project that relies on over 200,000 volunteers to classify and tag galaxies, found that sex had an influence on incentives. Men were more likely to volunteer on Galaxy Zoo because of an interest in science, while women were more likely to be motivated by fun and a desire to see beautiful galaxy images. Another study conducted by Chandler et al [7] to determine how the meaningfulness of a task affects the quantity and quality of data provided on Amazon's Mechanical Turk (AMT), indicated that ethnicity influenced volunteers responsiveness to task meaningfulness. They found that Indians were more motivated by financial benefits and less responsive to task meaningfulness than Americans were, and Americans were more motivated by fun than other groups. Yet another large-scale survey conducted by Kaufmann et al [27] studied the effects of demographics on usage of AMT. The study found that volunteers stating to still be in education ranked skill variety and social contact significantly lower than volunteers who were

gainfully employed. Thus, indicating that education does have an influence on the effectiveness of an incentive to motivate participation.

2.4.2 Participatory Sensing

There is currently no study on the influence of demographics on incentives in a participatory sensing context. The studies described in Section 2.4 have shown that demographics influence the effectiveness of an incentive to motivate participation in crowdsourcing and collective intelligence communities. Crowdsourcing and Collective Intelligence domains bear similarities with the participatory sensing domain, in that they also rely on volunteers from different demographic groups for data collection purposes. There is therefore reason to believe that demographics may also have an influence on incentive effectiveness in participatory sensing. However, as discussed in Section 1.4, there are distinct differences between these communities and participatory sensing. Participatory sensing has unique characteristics that do not necessarily apply to the other domains; users are often asked to repeatedly perform a participatory sensing task over time, which is not the case with collective intelligence and crowdsourcing. These differences may change how volunteers respond to incentives in a participatory sensing context.

Furthermore, it is likely that no single incentive will be effective at motivating and sustaining user engagement for all volunteers in a participatory sensing campaign. Yet, incentives for participatory sensing are still applied in a “one size fits all” manner. It can be argued that targeted incentive design can be more effective than incentives applied to the entire volunteer population, and an understanding of demographic

differences is essential for designing incentives for participatory sensing. Knowing which kinds of incentives to use with different user groups would presumably improve volunteer participation.

2.5 Summary and Research Contributions

In this literature review, the need for the consideration of demographic differences and how these factors influence volunteers' willingness to provide data to a campaign is highlighted. Also highlighted is the lack of research on the use of non-monetary incentives in the participatory sensing domain. The classification of non-monetary incentives into motivational categories from the Foggs Behavior Model in section 2.3.2.3, provide campaign organizers with a clear reference to non-monetary incentives and their possible applications for different campaigns and user types. This classification contributes to the participatory sensing domain by bridging the gap in the focus and use of monetary incentives.

Next, I attempt to understand the influence of demographics on volunteer motivation in participatory sensing and how different demographic groups respond to the incentive categories discussed above. The next chapter addresses the survey conducted to investigate the influence of demographics on the effectiveness of non-monetary incentives in participatory sensing. The objective is to investigate the influence of age, sex, ethnicity and education on the effectiveness of non-monetary incentives as promoters of volunteer participation.

CHAPTER 3: DEMOGRAPHICS INFLUENCE MOTIVATION IN PARTICIPATORY SENSING

This study aims to investigate demographic determinants of user engagement in participatory sensing. Its objective is to (a) identify non-monetary incentives and the influence of age, sex, ethnicity and education on their effectiveness as promoters of individual participation and (b) provide a mapping of incentives that are effective for each demographic group.

3.1 Hypotheses

1. The *age* of a volunteer is a factor in determining the effectiveness of incentives applied in a participatory sensing data collection campaign.
2. The *sex* of a volunteer is a factor in determining the effectiveness of incentives applied in participatory sensing data collection campaign.
3. The *ethnicity* of a volunteer is a factor in determining the effectiveness of incentives applied in a participatory sensing data collection campaign.
4. The *education* of a volunteer is a factor in determining the effectiveness of incentives applied in participatory sensing data collection campaign.

3.2 Study Methodology

To investigate the influence of demographics on the effectiveness of incentives in participatory sensing, a large-scale survey of 260 respondents was conducted. Given

the number of variables (age, education, sex, and ethnicity) in this study, the use of a survey method was justified because it provided an efficient means of measuring all the variables without substantially increasing the time or cost. Also, given that demographics is a main factor in this study, the use of a web-survey increased the potential for a wider demographic reach and a larger sample size; due to the simplicity and ease with which the survey could be e-mailed or shared with participants. Furthermore, this method allowed for a more streamlined and effective design.

Participants accessed the web-based survey through a hyperlink that brought them to <http://www.surveymshare.com>, an online survey platform. Before participating in the survey, participants were presented with a statement of informed consent and had to agree prior to continuing on to the main survey. The online-survey was active for a period of two weeks; no incentives were provided to the participants for taking the survey.

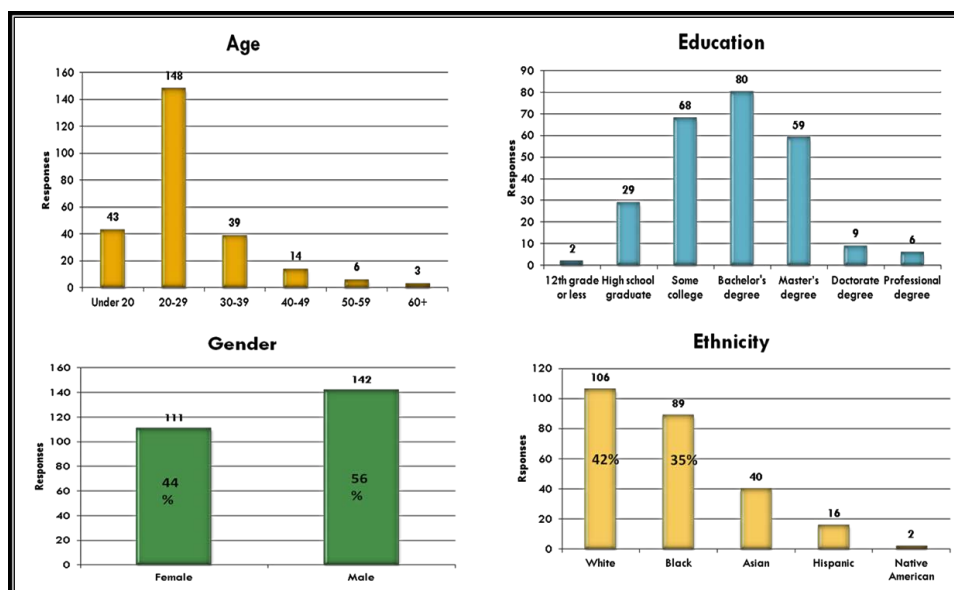
3.3 Sampling Technique

Survey participants were recruited using snowball sampling [2], a non-probability sampling technique in which study participants are recruited from acquaintances who in turn recruit others by word of mouth or social networks. Snowball sample was seeded through an email distribution list of faculty, staff and students, and also through the Facebook accounts of colleagues. Snowball sampling was chosen to specifically to increase the diversity and demographics of our sample.

3.4 Population and Sample Size

Two hundred and sixty responses were received. The sample of participants received for each demographic group were representative of the actual percentage of the groups in the general UNCC population.

Table 1: Demographics of survey participants



3.5 Survey Validity and Reliability

To test and improve the internal validity of the survey instrument in terms of the wording, ambiguity, order of the questions and the range of answers on multiple-choice questions, a pilot survey was conducted with 27 UNCC STARS Alliance members, including staff and students. Participants were asked to complete the survey and encouraged to ask questions while completing it. Where results indicated that a survey question was ambiguous, such survey items were modified. The survey was then reviewed by Computing and Informatics faculty members who are experts in

survey research and Human Computer Interaction. Their input was used to further revise the survey. The final version of the survey represented a satisfactory measure of the desired constructs, including incentives and demographics to be investigated. Data from the pilot survey was not used to test our hypothesis and was not included with data from the actual study during our analysis.

To test for survey reliability, Cronbach's Alpha was conducted to measure the internal consistency and reliability among the group of items combined to form a scale. The correlation coefficient was greater than (0.70) for the subscales identified. This suggests an acceptable internal consistency and reliability of the items used. Further details about Cronbach's Alpha conducted is described in Section 3.7.

3.6 Survey Design

The survey measured two phases of participation (a) Motivation to participate and (b) Engagement during participation. The survey asked participants to self-report on the likelihood of incentives provided to motivate and engage them in the real-world participatory sensing scenario provided below:

“Imagine you were asked to download and use a phone application that maps your daily routes to display your exposure to air pollution. This application uses your phone's GPS to upload your location traces to a secure server that will be analyzed by researchers. This information helps you interpret what your actions mean for your health, the health of others, and the environment. The data collection process involves 2-3 weeks of constant monitoring to provide adequate feedback.”

The questions asked included:

- Question 1: “How likely are the following to *motivate* you to participate in a 2-3 week data collection process such as the one described in the scenario above”
(9 survey items)
- Question 2: “How likely are the following to *keep you engaged* during a 2-3 week data collection process such as the one described in the scenario above”
(9 survey items)

Responses were on a five-point Likert scale with end points “1: Least likely” and “5: Most likely.” Participants were asked to report their age, sex, level of education and ethnicity in order to collect demographic data. Survey responses are analyzed across all four demographic variables.

3.6.1 Mapping of Motivation Categories to Incentives Items

The survey measures the following motivational factors:

- Social: The need for social involvement as a motivational factor is supported by various studies on behavior change, collective intelligence communities and volunteering. Fogg [16] defines this factor as the desire to belong to a stable framework of some ongoing relationship in which individuals share a mutual concern [16]. Paulini et al describes it as a desire to have a shared experience with one or more individuals or to be recognized within a community of peers [45]. This factor is also defined by Lampe et al [30] as the desire to belong, to be socially connected and to have a sense of value within a community.

Items measuring Social include:

- A chance to meet people and make friends
 - A chance to work as part of a team or community
 - Facebook wall posts about my contributions for friends and family to see
 - Opportunities to be visible and socialize
 - Ability to invite friends to participate as a group
 - Ability to collaborate as a team
 - Socializing and building relationships
- Learning: Learning as a motivational factor is supported by Clary et al [8]. Their work identifies the need for learning experience and value—an understanding of how meaningful or impactful performing a task is—as motivators for volunteer activities. Csikszentmihalyi [10] states that motivation is characterized by mastery, and approach-oriented striving to meet internal standards of excellence. According to Csikszentmihalyi, these strivings are experienced as curiosity and interest in learning something.

Items measuring Learning include:

- A chance to learn about exposure to emissions and how they relate to my actions
- Mere interest in the process of participating
- Continuous learning experience from participating
- A visual representation of my contributions (e.g. a map showing pollution levels along my route)

- Fun: Research by Csikszentmihalyi [10], also identifies fun as a motivational factor. In his work, Csikszentmihalyi defines a concept called “Flow”, a state in which a person is fully immersed and involved in the process of an activity, such that the action becomes so enjoyable and gratifying that people are willing to do it for its own sake, with little concern for what they will get out of it. Paulini et al [45] further describes this motivational factor as participation for entertainment, enjoyment, excitement, relief from other experiences, or simply furnishing the passage of time. Items measuring fun include:
 - I enjoy participating
 - A chance to have fun while performing a task

- Altruism: Altruism is defined as a desire to help others and the community [46], and research has shown that engaging in contributory activities help maintain life-satisfaction and psychological well-being [25]. Research by Clary et al [8] shows that volunteers are primarily motivated by the desire to help those less fortunate than themselves. Altruism is classified by this work as “enhancement”, stating that altruistic individuals are motivated by the enhancement of positive affect and personal development.
 - A desire to help the community
 - I would participate because I was asked to
 - A sense of civic duty
 - I want to feel accomplished
 - Doing something worthwhile

- Reputation, Recognition and Rewards: In his work on the Collective Intelligence Genome, Malone et al [34] underscores the importance of reputation in motivating participation in collective intelligence communities. Malone categorizes this as Glory, which is defined as recognition received from peers and the community. The reader to leader framework by Shneiderman et al [47] discusses the ability to build reputation, visible recognition and rewards over time as a significant motivation. Lastly, Fogg's behavior model emphasizes social recognition as a core motivational factor [16]. A user's understanding of the value of their contributions positively impacts motivation and contributions provided by that user.

Items measuring Reputation, Recognition and Rewards are as follows:

- A chance to build my reputation overtime
 - Recognition (e.g. a certificate) for your contribution
 - I want recognition for doing good things
 - A chance to receive rewards
 - Receiving rewards for my participation
 - I want prizes and rewards
- Challenge: In the reader to leader framework, Preece and Shneiderman [47] outline the evolution of technology-mediated social participation, in which participants evolve from contributor, to collaborator, and finally, to leader. This work cites the love of challenge as a key motivational factor to promote participation from reader to leader.

Items measuring Challenge include:

- A chance to challenge myself and use my skills
 - A data collection challenge/mission between participants
 - I want to challenge myself
- Feedback: Rashied et al [50] demonstrates that showing users the value of their contribution positively impacts motivation and contributions provided by that user in recommender systems. Items measuring Feedback include:

- Constant reminders of the value of my contributions

3.6.2 Mapping of Incentive Items to Actual Incentives Provided

To directly map from incentive items to the actual incentives that would be included in a participatory sensing application, the following question was added.

- Question 4 “Which of the following *features* is most important for you in a participatory sensing application” (7 survey items)

Some of the items included a leaderboard or point-based system (challenge), Facebook or twitter feeds(social) and visual representation of the data collected to show pollution levels(learning).

A summary of the categories of motivation used in this study, the description of incentives used as items in each of the categories, and the theoretical sources are reported in Table 2. The complete list of the survey questions and items used is given in Appendix A.

Table 2: Survey constructs and definitions adopted

Motivations	Survey Questions	Theoretical Sources
Social Acceptance & Rejection		
Reputation	A chance to build reputation over-time through volunteering	Malone [34], Shneiderman [47], B.J Fogg [16]
Recognition	A chance to be recognized for participating in something worthwhile	B.J Fogg [16], Shneiderman [47]
Social	A chance to meet people and make friends or a chance to collaborate as part of a team	B.J Fogg [16], Paulini [45], Lampe [30]
Pleasure & Pain		
Altruism	A desire to help other and the community, feeling accomplished for participating in something worthwhile or a sense of civic duty	Jane Allyn Piliavin [46]
Fun	A chance to have fun while performing a task or participation for entertainment, enjoyment, excitement, relief from other experiences, or simply furnishinh the passage of time.	Csikszentmihalyi [10], Paulini [45]
Learning	Mere interest in the process of participating	Csikszentmihalyi [10], Clary [8]
Feedback	Receiving clear unambiguous feedback about contributions or reminders about the value of ones contributions	Rashied [50]
Hope & Fear		
Challenge	A chance to use ones skills or a data collection challenge e.g. a mission with rules and scoring between participants	Shneiderman [47]
Rewards	A chance to receive something for participating e.g. redeemable points or gift vouchers	

3.7 Survey Analysis and Results

To summarize patterns of correlation among observed variables and reduce the number of variables to a smaller number of factors, Principal Component Analysis

with varimax rotation was conducted on the survey data. This ensured that only meaningful correlated variables were retained. The principal component analysis cleanly resulted in two reliable factors: (1) *social* and (2) *pleasure*. Cronbach's Alpha was positive for each factor (social (.82) and pleasure (.75)), suggesting an acceptable internal consistency and reliability of the items identified.

The first factor, *social*, included the following 5 items:

- Q1a. *A chance to meet people and make friends*
- Q2a. *A data collection mission between participants*
- Q2c. *Facebook wall posts about my contributions*
- Q2g. *Opportunities to be visible and socialize*
- Q2j. *Ability to collaborate as part of a team*

The second factor, *pleasure*, included the following items:

- Q1e. *A desire to help the community*
- Q1f. *Mere interest in the process of participating*
- Q1g. *A chance to learn about emissions and how they relate to my actions*
- Q2e. *Continuous learning experience from participating*
- Q2h. *I enjoy participating*

3.7.1 Demographic Predictors of Social and Pleasure Incentives

A subscale score was defined for each of the above factors, where a weighted sum of items was calculated. Using the subscale scores, multiple regression was conducted to determine the degree to which there was a correlation between the two motivational factors (social and pleasure) and the demographics of age, sex, ethnicity and education

respectively. Age was the only demographic group that had a significant correlation with social motivation. There was no significant correlation between any demographic group and pleasure, indicating that neither age nor any other demographic group had an influence on pleasure as a motivational factor. The breakdown of results is as follows:

Multiple Regression results showed that age was the only significant predictor of social motivation. This explains 2.7% of the variance ($R^2=.027$, $F(1,252)=8.016$, $p<.05$) ($\beta = 1.637$, $p<.01$). In other words, the age of a volunteer had an influence on how effective social incentives were to motivate participation in a data collection campaign.

3.7.2 Mapping of Social Incentives to Age Groups

Survey results suggest that there is a significant relationship between the age of a volunteer and the effectiveness of social incentives to motivate volunteer participation in a participatory sensing context. To further examine the relationships between age and social incentives, Cross tabulation and Chi-square tests were conducted. Cross-tabulations recorded the frequency of responses of age groups for each of the incentive items in the social motivation category. Table 3 below presents the frequency counts of each age group for each of the social motivation incentives and the respective Chi-square analysis.

Mission/competition among participants ranked highest as the likely motivator for participants under 30 (67% responded Likely). While, collaboration and teamwork ranked highest as the likely motivator for participants above 30 (81% responded

Likely). The difference in age group responses for collaboration/team work was significant, with Pearsons Chi-square test showing ($p < .05$). There was also a significant difference in age group responses for a chance to network with people ($p < .05$). Social Media was the construct that had the lowest percentage of Likely for both age groups (22% and 25.8% respectively).

Table 3: Cross Tabulation with Chi-Square: mapping of social incentives to age groups

Incentives	Under 30			Above 30			Chi-Square
	Likely	Neutral	Unlikely	Likely	Neutral	Unlikely	
Q1a: A chance to meet people and make friends	37%	29%	35%	48%	36%	16%	$p < .05$ 0.031
Q1b: A chance to work as part of a team and community	58%	24%	18%	74%	20%	6%	0.07
Q2a: A data collection challenge/mission between participants	67%	20%	13%	70%	20%	10%	0.69
Q2c: Facebook wall posts about my contributions	22%	27%	51%	26%	40%	34%	0.80
Q2g: Opportunities to be visible and socialize	44%	36%	20%	61%	27%	12%	0.12
Q2j: Ability to collaborate as part of a team	59%	27%	14%	81%	16%	3%	0.01

Although Age was the only demographic group that influenced motivation, and the remaining demographic groups were not found to be statistically significant pre-

dictors of motivation or engagement, the results for other demographic group are discussed briefly. Incidentally, the constructs of Collaboration/Teamwork and Mission/Competition consistently proved to be the most Likely social motivators for the remaining demographics of Gender, Ethnicity, and Education. Also, as with the Age results, Social Media as a motivator produced the lowest number of Likely or better responses for all demographic groups. Most participants regarded this construct as an Unlikely motivator, or felt neutral about it. For Gender, Collaboration/Teamwork was the social motivation factor with the highest number of positive responses for males (66.2% responded Likely or better), and Mission/Competition for females (with 70.3% responding Likely or better). Social Media as a motivator produced the lowest number of Likely or better responses for both males (19.7%) and females (27%). For Ethnicity, Mission/Competition was highest Likely motivator for Whites (68%) and those in the Other category (68.9%), whereas Collaboration/Teamwork was the highest for Blacks (74.2%). Social Media had the lowest percentage of Likely responses for all three ethnicity categories (White 22.6%, Black 25.8%, Other 18.9%). Lastly, for Education, Mission/Competition was again the highest for the remaining categories (Undergraduate 68.9%, Graduate 70.3%). Social Media as a Likely motivator only garnered 19.6% in the Undergraduate category, and 32.4% of the Graduate education category.

3.8 Discussion

Eighty one percent (81%) of the Above-30 participants found collaborative teamwork to be a Likely motivator, and 61%, found “opportunities to be visible and

socialize to be a Likely motivator. This could be because their social circles are more established than their younger counterparts, and they are more interested in working with, being visible to, and recognized by their established peers. This would explain why less than half (48%) of the responders who were age 30 or older found meeting people and making friends to be a Likely social motivator. On the other hand, you would then expect meeting people and making friends to rank higher on the list of Likely social motivators for participants under 30, but in our case, less than half (37%) of participants under the age of 30 reported this as a Likely social motivator. Perhaps volunteer campaigns are just not one of the environments where younger participants go to meet people, and they see this social outcome not as a motivator but as a by-product of a different goal: competing in a challenge against others (which was considered a Likely motivator by 67%, the highest percentage of any of the social motivators for this group).

Drawing from these observations, a few preliminary recommendations with regards to organizing volunteer campaigns can be made. For example, where desired participants are to be older-ages 30 and above, they should be recruited with their peers, such as through snowball sampling, given that they are more motivated to volunteer if it gives them the opportunity to be recognized by and socialize with their peers. Furthermore, a campaign organizer should provide these older participants with the opportunity to collaborate with one another by giving them avenues to invite their family and friends to participate with them. collaborating as a team had the highest response rate for those over 30, so anyone designing an app for this group of volunteers should start here. Concerning the motivation of participants who are under the

age of 30, a campaign organizer should support their desire to engage in competition by providing incentives such as leaderboards, challenges and missions, and appropriate rewards. Without any knowledge of, or preference for the age of participants, team-based competition is likely to be an effective approach to motivate participation across all groups.

3.9 Implications

A more general implication from the findings is that a single incentive provided in a participatory sensing campaign is unlikely to be effective in motivating all participants in a campaign. The results highlight the need for a more targeted approach to incentive design, where incentives are tailored to the characteristics of participants. This type of investigation is especially relevant where increased user-generated content and active participation is crucial for advancing participatory sensing. Campaign organizers can draw from this knowledge of what motivates participants, to present participatory sensing campaigns in ways that will appeal to volunteers. Incentive designers can leverage these in heuristics to design incentives that are tailored for user groups.

3.10 Limitations

While Snowball sampling was a useful strategy to gain access to certain hard-to-reach demographic groups on a university campus, the use of this method resulted in very little control over the subjects that were selected for the study. Due to this, the true distribution of the population is unknown and accurate representation cannot be guaranteed.

3.11 Summary and Research Contributions

In this chapter, the hypothesis that age, sex, ethnicity and education have an influence on the effectiveness of various incentives to promote volunteer's participation in a data collection campaign was evaluated. A survey of 260 respondents randomly selected using snowball sampling was conducted. An analysis showed that the demographic of *age* significantly predicts social motivation and the effectiveness of social incentives in participatory sensing. The focus on demographics in the study of incentives in participatory sensing and the mapping of incentives to age groups is a valuable addition to the body of work in participatory sensing. The application of these findings can potentially enhance designers' efforts to motivate and engage participants, which in turn improves the quality and quantity of data provided to participatory sensing campaigns. The specific contributions of this survey to the field of participatory sensing can be summarized as follows:

- Evidence that supports the hypothesis that age influences the effectiveness of incentives to motivate data collections in participatory sensing.
- An understanding of the implications of age on the effectiveness of social incentives to motivate participatory sensing data collection campaigns
- A mapping of social incentives to age groups

An understanding of the demographic differences of participants and its influence on motivation may serve as a first step toward participatory sensing systems that can tailor incentives to encourage quantity and quality data collection from diverse

participants.

In the next chapter, a framework is developed to provide a generalized reusable solution for incentive selection in participatory sensing. This framework, called 4WT, serves as a building block for the thoughtful selection of incentives for different user types and application contexts in participatory sensing.

CHAPTER 4: TOWARDS A FRAMEWORK FOR PARTICIPATORY SENSING INCENTIVE DESIGN

While the application of incentives for participatory sensing shows promise, the theoretical foundation for designing and selecting incentives is lacking. To date, incentives for participatory sensing applications have been developed largely in isolation as siloed approaches. Incentives are typically designed from an application specific perspective, and applied singularly. This approach makes it increasingly difficult to design and tailor incentives in ways that maximize quality data contributions across the domain.

In this chapter, I propose a generalized reusable approach for incentive selection in participatory sensing. This approach is represented by a framework called 4WT, which allows application developers to identify a set of candidate incentives that are suitable for particular demographics of participants and types of applications. 4WT was developed based on theories in motivation and engagement and is also based on evidence of the influence of demographics supported by the survey findings in Chapter 3. The 4WT framework presents relationships among the following variables: *Who* is volunteering? *Why* should they volunteer? *What* incentives should be provided? *When* should incentives be provided? and *Triggers*, a concept that is particularly relevant in motivating sustained participation in participatory sensing campaigns. Using the framework, a campaign organizer can carefully consider the

characteristics of volunteers, as well as the inherent properties of the campaign, and judge the relevance of incentives to their own specific purposes. Incentives can then be manipulated in ways that are tailored for a particular application and its collection of users.

4.1 Related Work

The 5WH (Why, When, Where, What, Who, How) principle is a framework for representing information needs that are essential to an application or task [4]. This principle has been applied across many domains including context-aware services [5], investigative inquiry and journalism [56]. More closely related to participatory sensing, Bisdikian et al. [4] applied the 5WH metrics to assess the quality of information (QoI) for specialized, fixed location sensor networks, providing ways to assess the accuracy, timeliness, integrity, certainty, and confidence of high-level information produced by the sensors. In their approach, 5WH was used to summarize the information needs of an application into pieces of meta-information to aid the application decide if the provided information was compatible, relevant and fit-to-use for its own purpose. The 5WH approach has also been applied by Malone et al [33] to develop the Collective Intelligence Genome, a framework that identifies underlying building blocks known as “genes” —in the form of Who, What, Why and How— for designing successful collective intelligence systems. Given the success of the 5WH approach for determining quality of information in sensor networks and developing successful collective intelligence systems, I draw on this to develop the 4WT framework for participatory sensing incentive design. To motivate each part of the framework, I draw

on the theories of motivation and engagement discussed in Section 2. A description of these theories and how they apply are discussed in the respective sections for which they apply.

A contribution of this work is the application of these concepts using different factors, for a different purpose, in a different domain. The 4WT, shown in Figure 12, is focused on the design of incentives for volunteers in a participatory sensing context.

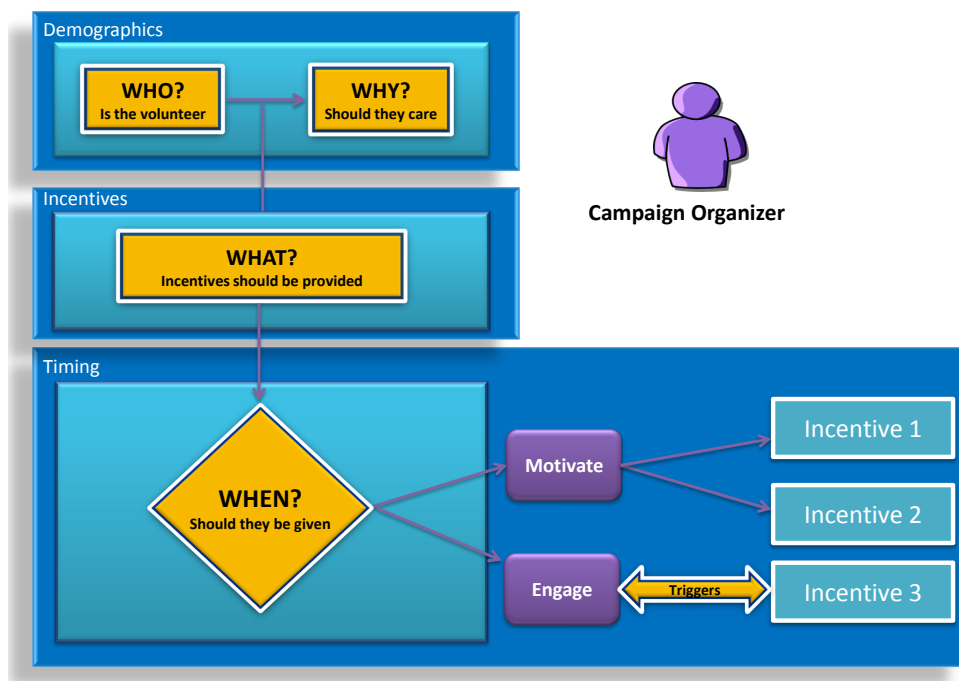


Figure 1: 4WT framework

4.2 4WT Framework for Incentive Selection

4.2.1 *Who* is the Volunteer

Knowing your volunteers includes understanding the demographic composition of volunteers needed for a campaign. Knowledge of the volunteer could help the campaign organizer to make informed decisions about what information to provide and

what kind of supporting details are necessary for the volunteer to understand the campaign and the importance of their contributions.

4.2.2 Why Should They Care

In their work on understanding volunteer motivations, Clary et al [8] outlines the need for learning experience, the need to exercise one's skills, the need to develop social relationships and value—an understanding of how meaningful or impactful performing a task is—as motivations for volunteering. This indicates that volunteers are drawn to causes that are relevant to them or valuable to their interests. Drawing from this, it could be concluded that based on a campaign organizers understanding of *Who*, they can identify why the campaign is valuable to the volunteer, explicitly highlight the benefits of participation and find the right hooks to grab their attention.

4.2.3 What Incentives Will be Provided

Fogg's Behavior Model was designed to help researchers and designers think systematically about the different factors that influence motivation, and explore different ways to motivate participation [16]. According to FBM, the core motivators of *social acceptance and rejection, pleasure and pain, and hope and fear* represent what motivates human behavior. Drawing from this, if behavior is motivated by the above factors defined in FBM, it could be inferred that volunteer motivation in participatory sensing can be increased by providing incentives that appeal to these core motivators. In Chapter 2, incentives used in participatory sensing applications were outlined and classified under these core categories of motivators. Using this model, campaign organizers can explore the appropriateness of these factors for their campaigns and select

corresponding incentives to appeal to volunteers. Incentives should be determined based on *Who* and an understanding of *Why*.

4.2.4 When Should Incentives be Provided

The theory of Burnout and Engagement explores both negative and positive states of worker and volunteer experiences. According to the Theory of Burnout and Engagement, although an individual may be motivated to perform a job at one point, over the course of time, they tend to experience detachment, reduced efficacy and exhibit high levels of absenteeism. Studies on burnout and engagement in various domains including education and technology adoption have proven that individuals lose resources overtime when they encounter stress, leading to loss of motivation and reduced efficacy. One strategy for preventing burnout is to build engagement. Engagement is characterized by strong involvement and high levels of willingness to invest effort in a job.

From TBE, it can be inferred that although an incentive was effective at motivating initial participation, the same incentive may not be sufficient to sustain continuous user engagement. Therefore, incentives could be targeted for different phases of participation. Establishing the role of an incentive will determine when it should be provided to the user; sequencing is key.

4.2.5 Triggers

Studies on sustaining motivation address the need for mobile applications to provide mechanisms such as reminders to support user engagement. Fogg [16] emphasizes the need for triggers, which is defined as periodic or persistent reminders to perform

the desired task. In a study conducted on diet, stress, and exercise related risk factors for cardiovascular disease in young mothers, moms were provided with the mobile app Ohmage [60] and asked to complete surveys 4 times a day using the app. Ohmage prompted participants to report their diet, stress, mood and exercise routines using temporal and spatially triggered reminders. One of such prompts reminded participants to charge the phone after the last survey of the day was reported. This was found to be very helpful throughout the duration of the six month study. Trialist [60], an application that supports personalized research for monitoring pain treatment, also provides support for daily, weekly and event-based reminders. The app informs patients when to begin and switch treatments, daily/weekly reminders for patients to enter clinical survey data, and periodic reminders about the time-left on the current treatment.

In participatory sensing, volunteers need support to remember the initial goal and maintain a consistent vision of the rewards of reaching that goal. It is important for campaign organizers to build in triggers in order to sustain participation. Other forms of richer multimedia prompts such as video and audio, and visualization should be supported. Incentives could also be used as triggers at various stages of participation.

4.3 Summary and Research Contributions

The absence of a framework for identification of variables that influence the effectiveness of incentives in participatory sensing posed a challenge to the design of result oriented sensing applications. This inadequacy created gaps in the process of developing and targeting incentives to encourage sustained participation. In this

chapter, I developed a preliminary framework that takes into account user characteristics, application characteristics, and the usage lifecycle of participatory sensing applications to enable more thoughtful selection of incentives that are effective for motivating quantity and quality data collection activities. Understanding these influences can help developers to create incentives that are tailored for an application and even personalized for a user.

A contribution of this work is the validation of an existing framework—5WH—applied to sensor networks and collective intelligence, to the participatory sensing domain, and the application of the framework for the participatory sensing using different factors. More specifically, the contributions of this work to the participatory sensing domain are as follows:

- Providing an adaptive approach that enables campaign organizers select different types and combinations of incentives to meet the needs of the campaign and cater to the demographic characteristics of volunteers
- Laying the groundwork for future research in developing incentive mechanisms that are effective at ensuring continued volunteer participation and at motivating quantity and quality data collection

In the next chapter, I present two user studies conducted using participatory sensing applications (a) Foodie Frenzy and (b) Watch it Bloom, which were developed and deployed on the University of North Carolina Charlotte (UNCC) campus. The first user study, Foodie Frenzy, was conducted to validate the survey findings in Chapter 3, in a real-world participatory sensing context, where participants bear the actual burden of volunteering in a data collection campaign. The second user study, Watch it

Bloom, was conducted to show transfer of findings to a different application domain. The findings from both studies are applied to develop a taxonomy of incentives that are likely to be effective for different demographic groups, and to create incentive selection guidelines for participatory sensing campaign organizers.

CHAPTER 5: THE INFLUENCE OF AGE ON MOTIVATION AND ENGAGEMENT IN PARTICIPATORY SENSING

Given the self-report nature of the previous survey, further studies were necessary to validate the survey findings in Chapter 3, which showed that age had a significant correlation with social motivation and that age was not a predictor of pleasure as a motivator. In this chapter, the findings of the survey are validated through a user study, conducted using a participatory sensing application called Foodie Frenzy. The user study followed three main steps: (a) A pre-survey to measure initial motivation for using the Foodie Frenzy application, (b) A Foodie Frenzy participatory sensing campaign, where participants were required to use the application for a three week period and (c) A post-survey to determine if the initial motivation was sustained after three weeks of use.

Furthermore, a second user study was conducted using another participatory sensing application called Watch it Bloom, in a different domain. The Watch it Bloom user study investigates the transfer of findings from Foodie Frenzy to a different domain. The Watch it Bloom study was conducted using the same steps described for the Foodie Frenzy application above. Both studies were conducted in the University of North Carolina Charlotte campus, to account for the same demographics of users.

The user studies addressed the following questions:

- Does age also have an influence on social motivation in a real world participatory

sensing context?

- Does age have an influence on pleasure motivation in a real-world participatory sensing context?
- Is there transfer of findings between two different application domains?

5.1 User Study 1: Foodie Frenzy Application

Foodie Frenzy is an Android based participatory sensing application that promotes dietary guidance. The app enabled participants to track their daily nutritional intake by taking pictures of their meals three times a day. For each picture taken, participants were required to report the percentage of the nutritional make up of their meals (e.g Protein, Grains, Vegetables, Fruit and Dairy) using sliders. Each food group was assigned a percentage and a weight (None, Some, Ideal). Percentages used were derived from the Center for Nutrition Policy and Promotion (CNPP), established in 1994 to improve the nutrition and well-being of Americans. The total score for each participant was determined by the percentage assigned to each food group selected, multiplied by the weight entered by the participant. Submitted photos were uploaded to a server for approval.

The Foodie Frenzy application implemented a number of different incentives, each of which were mapped to either the social or pleasure motivation categories. These incentives were applied throughout the entire duration of the study. Users were asked to complete a survey upon downloading the application and a post-survey after three weeks of using the application. These surveys were used to acquire users' demographic information and to elicit a self-reported measure of the effectiveness of

incentives before and after using the application. The pre and post surveys used can be found in Appendix B and C respectively. To show transfer between the previous survey and the Foody Frenzy survey, the questions asked in the Foodie Frenzy survey were directly mapped to the factors resulting from the principal component analysis that were analysed in the previous survey. Questions were mapped to the social and pleasure category and the same incentives under those categories were accounted for. However, the questions were shortened to enhance user experience on the mobile device.

Social motivation was targeted in the application using the following incentives:

- Facebook and Twitter Wall posts: Participants were given the option to share their images to Facebook and Twitter. By clicking on the Facebook or Twitter icon in the app, participants were directed to Facebook and Twitter respectively, to view their images and that of others
- Competition with other Participants: Participants received points based on the nutritional value of the meal they captured. A leaderboard featured the top ten participants with the most nutritious meals

Motivating users with incentives from the pleasure category was accomplished by asking participants to help contribute to research. See the recruitment flyer in Appendix F.

5.1.1 Recruitment

Twenty four faculty and student volunteers were recruited to download and use the Foodie Frenzy application. Recruiting was done in collaboration with Chartwells,

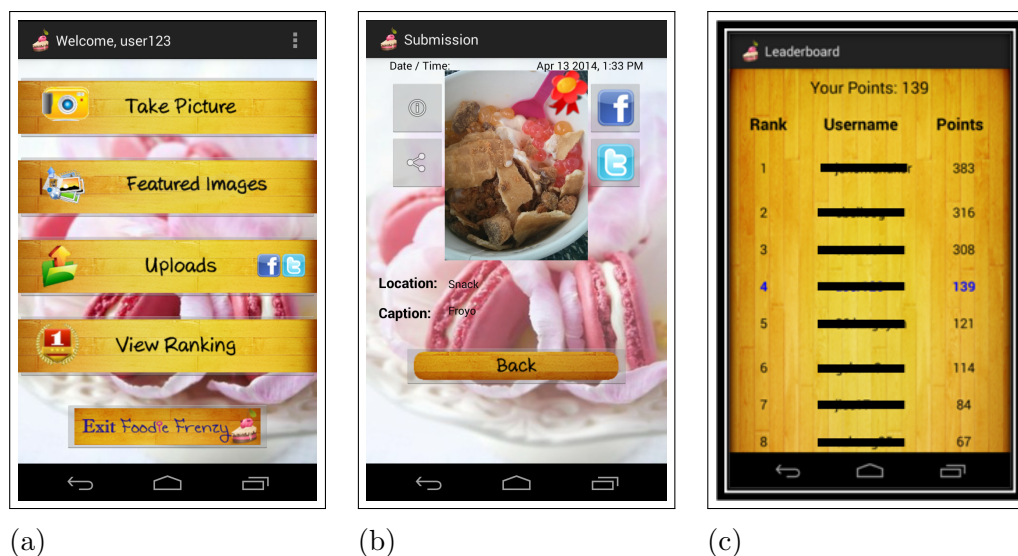


Figure 2: Screen shots of the Foodie Frenzy application: (a) Foodie Frenzy home page (b) Facebook and Twitter features (c) leaderboard feature

UNCC's food service partner. The app was advertised alongside their Balanced U program, which posts nutrition facts for menu items online and in dining halls. Recruiting was also done in collaboration with the International Students Office (ISSO), Non-Traditional Students Organization (NTSO) and the Office of Volunteer Outreach. Emails containing a description of the application and an attached flyer and link to download the app were disseminated through multiple listserves. The study ran for a period of five weeks.

5.1.2 Foodie Frenzy Pre-Survey

A pre-survey was used to determine the initial motivation of participants to use the application. The questions used to measure motivation in the pre-survey include:

- Question 1: "Why did you choose to use the Foodie Frenzy app". This question involved 5 items with responses on a 3 point scale ("1: Yes", "2: No", and "3: Maybe")

- Question 2: “What do you look forward to while using the Foodie Frenzy application.” This question involved the same five items in question 1. Participants responded by choosing one option using a radio box.
- Social motivation was measured by the following two items:
 - To share my daily food photos on social media
 - To compete with other participants on a leaderboard
- Pleasure as a motivator was measured by the following three items:
 - I was asked to participate
 - To contribute to research
 - To learn about my daily food choices

Participants were asked to report their age, sex, level of education and ethnicity. Because design guidelines for the 4WT are generated from the survey, which showed that age and social motivators were correlated, the user study analysis focuses on age.

5.1.3 Foodie Frenzy Post-Survey

To determine if the initial motivation was sustained after three weeks of using the Foodie Frenzy application, the post-survey asked the following questions:

- Question 1: “Why are you still using the Foodie Frenzy app?” This question involved the same 5 items provided in the pre-survey. Responses were also on a 3 point scale “1: Yes”, “2: No”, and “3: Maybe.”
- Question 2: “Please rank the features you enjoyed most while using the Foodie Frenzy App” This question also involved the same five items in the pre-survey,

which participants ranked on a scale of Most Engaging to Least Engaging

5.1.4 Foodie Frenzy Results and Analysis

To determine the effect of age on motivation and user engagement, analysis focused on accessing the number of participants who responded “Yes” or “No” to each of the items and the degree to which their responses varied by the age groups. Furthermore, a comparative analysis of responses in the pre and post survey was conducted. The breakdown of the overall sample and age of participants in the Foodie Frenzy study is provided in Figure 3.

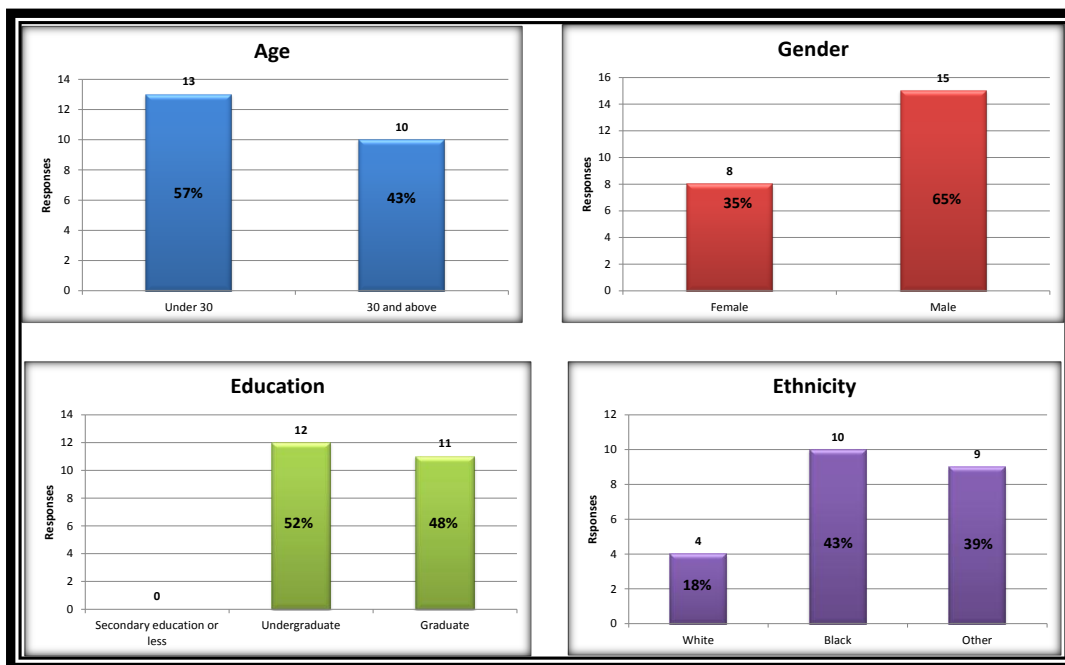


Figure 3: Foodie Frenzy demographic distribution

5.1.4.1 Foodie Frenzy Pre-Survey Results

Pleasure was the number one motivating factor for both age groups to participate. For question 1: “Why did you choose to use the Foodie Frenzy app,” Q1e “To contribute to research” was the number one reason why participants were motivated (see

Figure 4a), with 92% of under 30 and 90% of above 30 responding “Yes.” Only 46% of participants under 30 and 40% of participants 30 and above responded positively to learning as a motivator, as shown in Figure 4b. No significant difference in the responses of age groups was found for questions in the pleasure motivation category, confirming findings from the large-scale survey, that age is not a significant predictor of pleasure as a motivator.

Conversely, social motivation received the lowest percentage of positive responses from both age groups. For Q1c: “Ability to share my daily food photos on social media,” only 31% of under 30 and 0% of 30 and above responded “Yes”, as shown in Figure 4c. This difference in age group responses was significant, with $p < .05$, also confirming findings from the large scale survey that age is a predictor of social motivation. The ability to compete with participants on a leaderboard (see Figure 4d) also received a low number of positive responses. Only 23% and 3% of under 30 and 30 and above responded “Yes.” respectively.

For question 2: “What do you most look forward to while using the Foodie Frenzy application.” Participants were asked to choose one answer from a list of items representing both pleasure and social motivation. Analysis focused on understanding what participants in each age group reported as their top motivator. Results showed that “helping out the research community” received the highest frequency of responses from both age groups, confirming pleasure as their initial motivation for participating.



Figure 4: Foodie Frenzy pre-survey results (a) contribute to research (b) learning (c) sharing images on social media (d) competition

5.1.4.2 Foodie Frenzy Post-Survey Results

Analysis of the Foodie Frenzy post survey was conducted to investigate the difference in responses of age groups from pre-survey to post-survey. Results showed that although both age groups were initially motivated by the pleasure factor in the pre-survey, participants under 30 required a social factor to ensure their continued participation. While participants above 30 maintained the same motivation during

the three weeks of using the application. The breakdown of results is as follows:

For question 1: “Why are you still using the Foodie Frenzy application,” there was an increase in the desire for social factors as motivators from pre-post survey, for participants under 30. Fifty seven percent rated “the ability to share my daily food photos on social media” as the number one reason for continued participation, as seen in Figure 5c. There was also an increase in the desire to compete on a leaderboard from pre-post survey for this age group, 36% responded “Yes” in the post-survey (see Figure 5d), compared to 23% in the pre-survey.

Also for participants under 30, there was a decrease in the desire for pleasure factors as motivators from pre-post. Only 50% responded favorably to the desire to contribute to research, compared to 92% in the pre-survey. The same applied to learning, reducing from 46% in the pre-survey to 36% in the post. Although favorable responses to the desire to contribute to research decreased from pre-post survey, this was still considered a high motivator for the under 30 demographic group, as shown in Figure 5a.

Participants 30 and above maintained the same initial motivation for participating. Pleasure factors remained the highest motivators, with (89%) responding “Yes” to the desire to contribute to research. The desire for Learning remained the same from pre-post survey. In the social motivation category, same as the under 30 group, there was a moderate increase in the desire for social factors as motivators for this age group. The the ability to share my daily food photos on social media increased from (0%) in the pre-survey to (33%) in the post-survey. The desire for competition on a leaderboard also increased from (10%) in the pre-survey (to 33%) in the post-survey.

These results are shown in Figure 5. For question two, when asked to rank the features enjoyed most while using the Foodie Frenzy App, no statistical difference was found between responses for age groups.



Figure 5: Foodie Frenzy post-survey results (a) contribute to research (b) learning (c) sharing images on social media (d) competition

5.1.5 Discussion

The user study recruited 24 faculty, staff and students at the University of North Carolina Charlotte (UNCC). User study results showed that the number one moti-

vational factor for initial participation was pleasure, indicated by participants' self-report on their desire to contribute to research. These results showed no significant difference in the responses of different age groups. Given that the study was conducted in a research community, this initial motivation could be explained by The Theory of Planned Behavior (TPB) [1], which proposes that an individual's behavior in any given situation is determined by the individual's attitude towards the behavior, the measure of their own competence to complete the task, and social attitudes/environmental factors such as the perceived consequence and implication of performing the task.

Social motivation as a factor, indicated by participants' self-report on the desire to share their daily food photos on social media, received the least favorable response as a motivator for initial participation. Based on our study, these results suggest that the use of Facebook was not an effective incentive to target initial motivation. These findings are supported by studies which have shown that an incentive different from the intrinsic motivation for performing an activity may replace the intrinsic motivation, and possibly reduce the overall motivation to perform the task.

For continued participation, there was a shift in responses for participants under age 30. Although the desire to contribute to research was the most likely factor to motivate this group of users, the number one factor to keep them engaged was the ability to share daily food images on Facebook. Although ages 30 and above recorded a moderate increase in the likelihood of social motivation as a factor for continued participation in the post-survey, the desire to contribute to research remained the most likely reason for their continued participation. These results provide some insight

in to the different phases of motivation experienced by volunteers during participation. The difference in age group motivation and engagement from pre-survey to post-survey is shown in Figure 6.

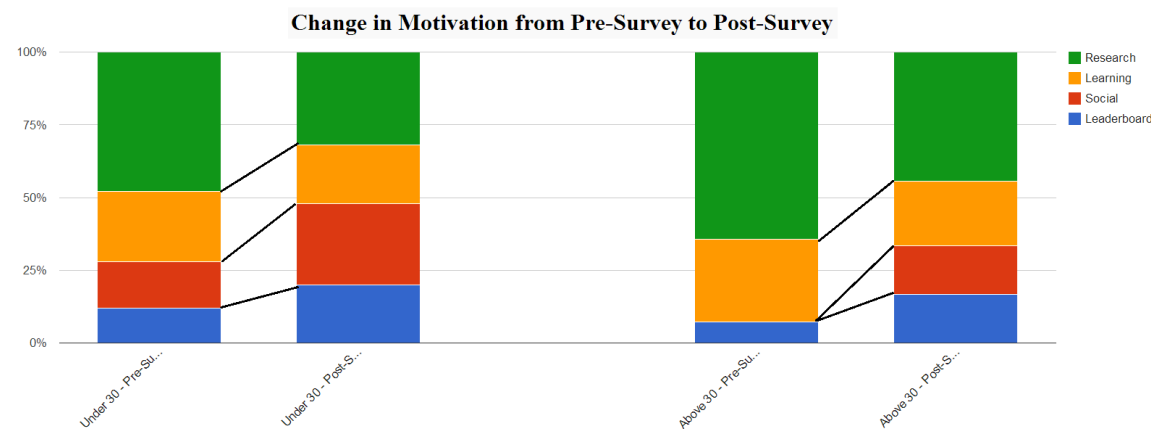


Figure 6: Foodie Frenzy: change in age group motivation from pre-survey to post-survey

5.2 User Study 2: Watch it Bloom Application

Watch it Bloom is an Android based participatory sensing application that promotes the knowledge and appreciation of plants for educational and aesthetic purposes. The application enables participants to monitor phases of plant growth by capturing images of plants every day. Each photo taken was geo-tagged and time-stamped and uploaded to a server for approval. For every approved photo, participants received 10 points. Approved images for all participants were represented on a map showing the various locations where photos were taken.

The study design and procedure, incentives embedded in the application, as well as the same pre and post surveys described for Foodie Frenzy in Section 5.1.2 and 5.1.3 respectively, apply here. Screen shots of the Watch it Bloom application are shown in Figure 7.

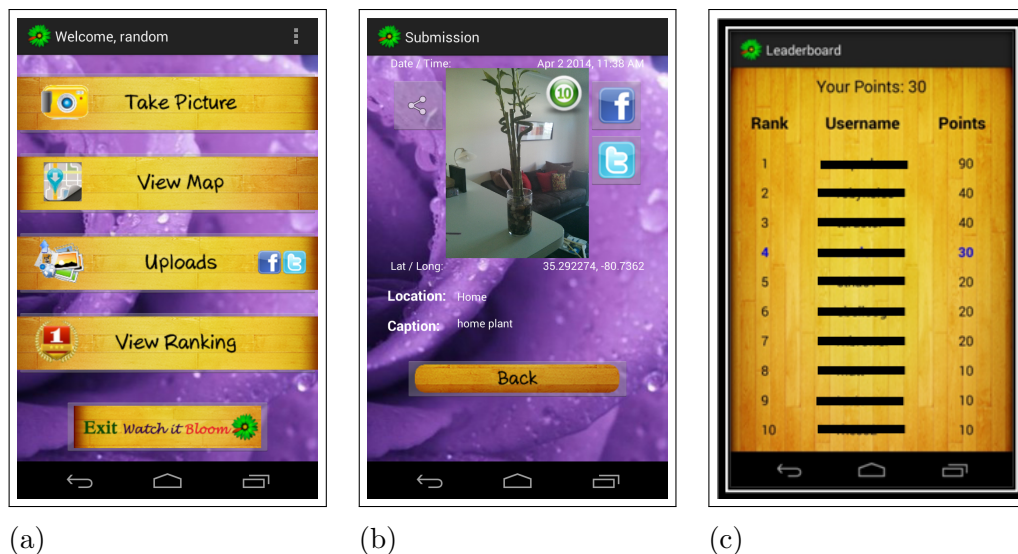


Figure 7: Screen shots of the Watch it Bloom application: (a) Watch it Bloom home page (b) Facebook and Twitter feature, (c) leaderboard feature

5.2.1 Recruitment

Faculty and student volunteers were recruited to download and use the app. Recruiting was done in collaboration with the UNCC Botanical Gardens. Recruiting was also done via the International Students Office (ISSO), Non-Traditional Students Organization (NTSO) and the Office of Volunteer Outreach. Emails containing a description of the application and an attached flyer and link to download the app were disseminated through multiple listserves.

5.2.2 Watch it Bloom Analysis and Results

Similar to Foodie Frenzy, analysis focused on understanding the number of participants who responded yes or no to each of the items and the degree to which they were related to age. The breakdown of the overall sample and age of participants is provided in Figure 8.

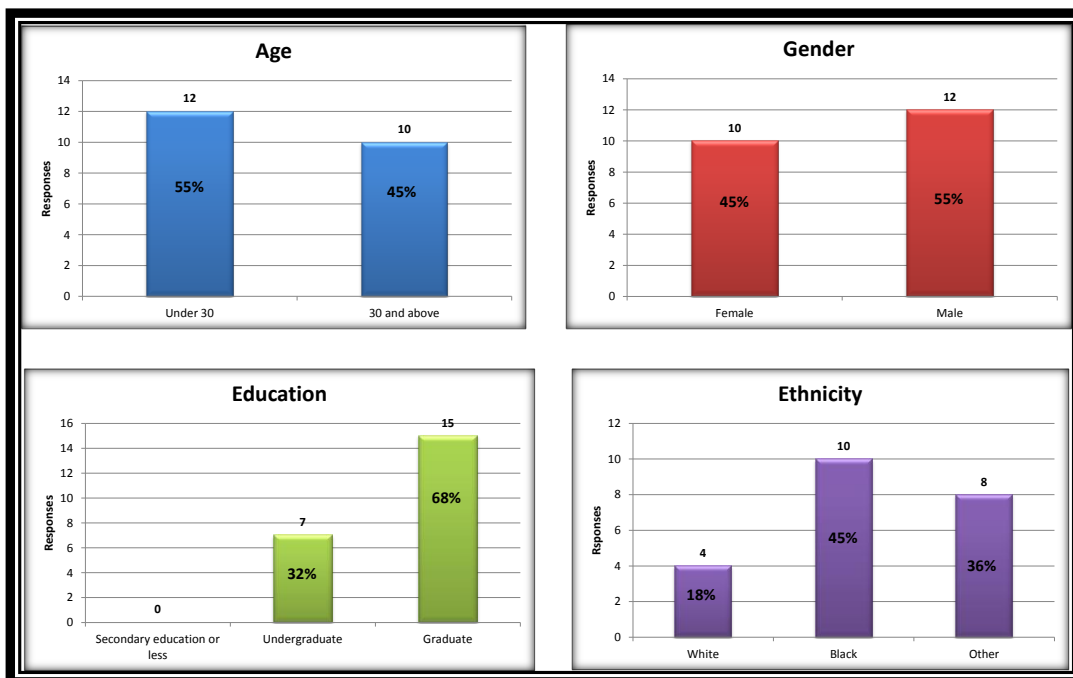


Figure 8: Watch it Bloom demographic distribution

5.2.2.1 Watch it Bloom Pre-Survey Results

Watch it Bloom results for the pre-survey reflects findings of the Foodie Frenzy application. Pleasure was the number one motivating factor for both age groups to participate. For question 1: “Why did you choose to use the Foodie Frenzy app,” Q1e “To contribute to research” was the number one reason why participants were motivated (see Figure 9a), with 83% of under 30 and 90% of above 30 responding “Yes.” Results also show that there was no significant difference in the responses of age groups for pleasure motivation. Social motivation received the lowest percentage of positive responses from both age groups. For Q1c: “Ability to share my daily food photos on social media,” only 33% of under 30 and 20% of 30 and above responded “Yes”, as shown in Figure 9c.

For question 2: “What do you most look forward to while using the Watch it Bloom

application?” Helping out the research community also received the highest frequency of responses from both age groups, mirroring results of the Foodie Frenzy application.

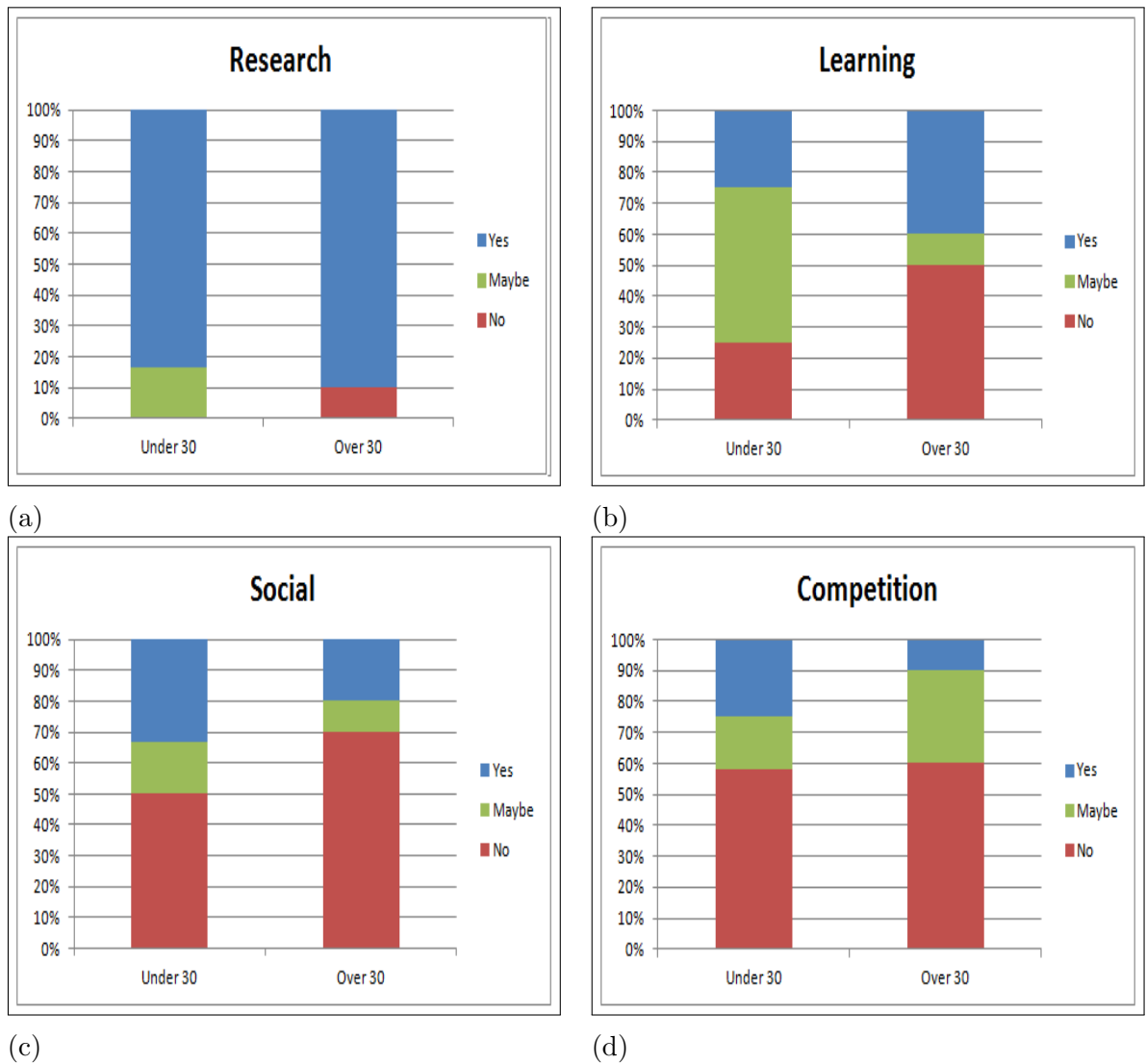


Figure 9: Watch it Bloom pre-survey results (a) contribute to research (b) learning (c) sharing images on social media (d) competition

5.2.2.2 Watch it Bloom Post-Survey Results

The Watch it Bloom post-survey also focused on investigating the difference in responses of age groups from pre-survey to post-survey. Results showed that although both age groups were initially motivated by the pleasure factor in the pre-survey,

participants under 30 required a social factor to ensure their continued participation. While participants above 30 maintained the same motivation during the three weeks of using the application.

Analysis for question 1: “Why are you still using the Watch it Bloom app?” showed an increase in positive responses for social factors as motivators, and a subsequent decrease in positive responses for pleasure factors as motivators from pre survey to post survey, for the under 30 age group. Responses for this group of participants increased positively from pre-survey (33%) to post-survey (50%) for Social media, shown in Figure 10c, and also for Leaderboard (25%) to (50%) respectively, shown in Figure 10d. Pleasure factors such as learning, decreased from pre-survey (25%) to post-survey (8%) as seen in Figure 10b.

Although the above 30 age group also showed a slight decrease in learning as a motivator from pre-post survey, this group maintained the same pleasure motivation, Q1e “To contribute to research,” throughout the duration of the campaign. With 100% responding positively to the question, as seen in Figure 10c.

The demographics of participants involved in the two user studies was a ratio of 1:1. That is, there was an equivalent amount of under 30 participants for both apps (13 out of 23 using Foodie Frenzy compared to 12 out of 22 using Whatch it Bloom). The same was the case for participants 30 years of age and above (10 out of 23 compared to 10 out of 22). Investigation of the initial motivation of participants showed similar findings from the Foodie Frenzy application to Watch it Bloom. For both applications, pleasure was the number one motivational factor for initial participation, where helping out the research community was ranked the highest motivator.

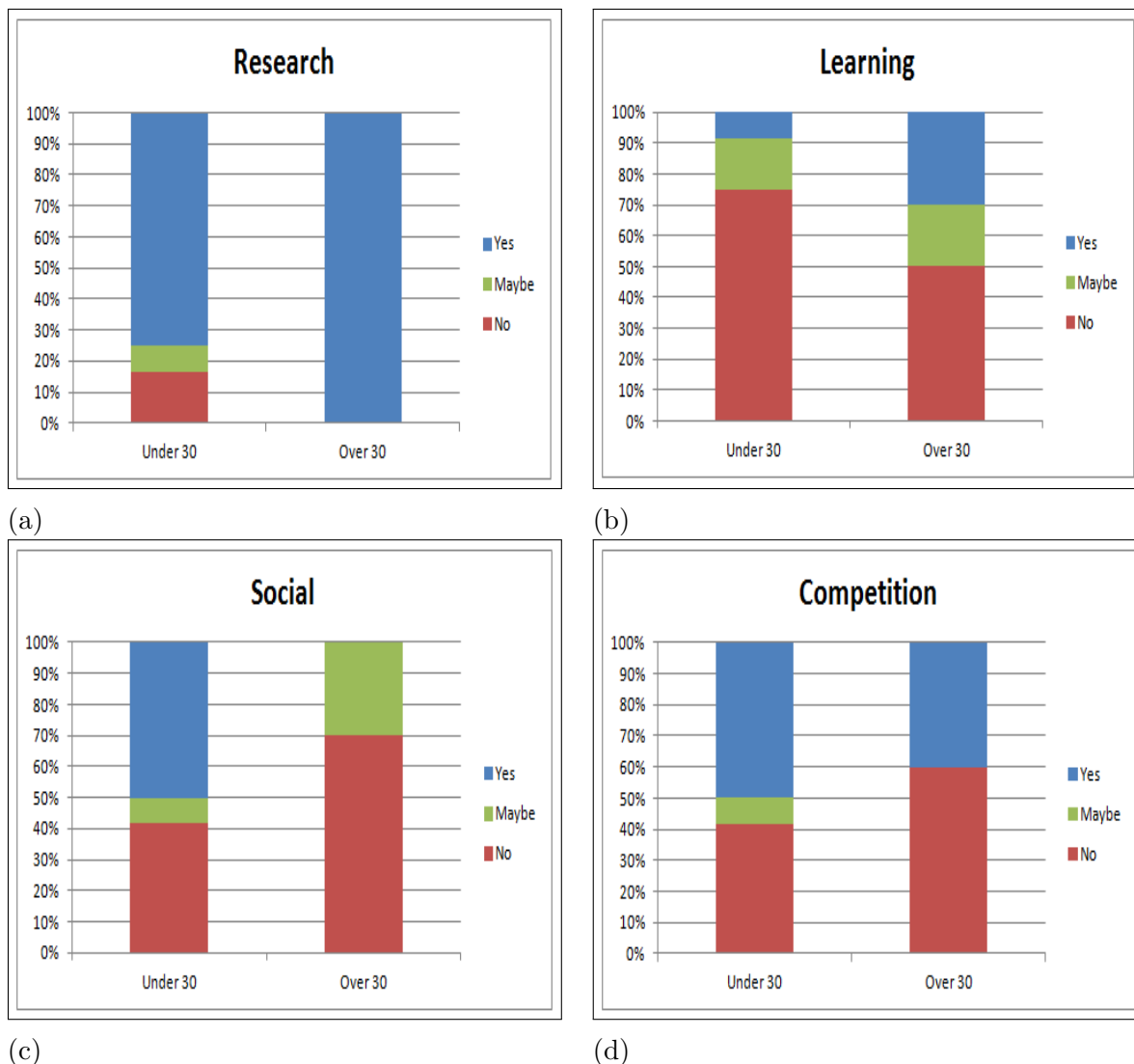


Figure 10: Watch it Bloom post-survey results (a) contribute to research (b) learning (c) sharing images on social media (d) competition

For continued participation for the three week duration of the studies, there was a shift in motivation for the under 30 age group from pleasure as a factor to social as a motivational factor, while ages 30 and above maintained the same initial motivation through the study duration, for both applications.

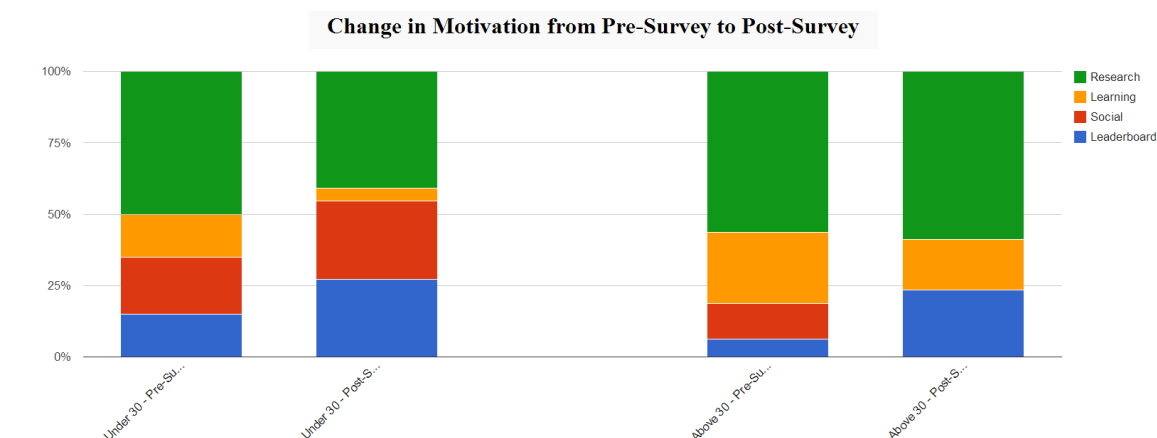


Figure 11: Watch it Bloom: change in age group motivation from pre-survey to post-survey

5.3 Overview of App Usage

Insight into general use of the applications was gained by looking at usage data and interviewing a few participants. For Foodie Frenzy, participants submitted pictures of their food on an average of twice a day. Users consistently submitted photos daily, but number of submissions each day were dependent on a number of factors, such as how many meals a day the individual had, and the aesthetic value of the meal. One participant reported an eagerness to post their food to Facebook if their meal was healthy or looked particularly good and appetizing, and would therefore be socially approved. *“I was more likely to submit pictures of my food if it looked yummy or healthy because I figured those would get me more likes by people who saw them.”* Users of the Watch it Bloom application submitted photos of plants on an average of once a day. For example, a participant who owned a household plant consistently took a picture of the plant once a day, but did not often submit photos of other plants. On the other hand, another participant without a household plant

went out of his way to take pictures of plants, which typically resulted in more than one submission a day. Overall, week one saw very limited usage of social networks from participants using both apps. For example, a participant reported hesitation to post pictures of plants to FB and Twitter in the first week because it did not align with her typical posted content. However, from week two, there was an increase in the use of social media from participants, mostly under 30. One such participant said *“Plants are not something I typically notice or post about on Facebook, but after using the app a few times, I found a new appreciation for nature. I began looking forward to finding beautiful plants that I could take pictures of and share with my friends.”* The same participants who began to post to Facebook continued to do so throughout the campaign’s duration.

5.4 Study Limitation

Due to the small sample size in the user studies, these results must be interpreted carefully. We acknowledge that while we believe there is most likely a real and moderate effect, there are insufficient results to draw a reliable conclusion that can be applied to the general population. Similarly, for those demographic factors that did not prove statistically significant, the lack thereof does not mean there is no effect; a study with a larger sample size is needed to draw such conclusions. All in all, the data from these studies could be used to design larger confirmatory studies to reinforce the effects suggested here.

5.5 Mapping of Incentives to Demographic Groups

Demographic responses to incentives that motivate and engage the study participants are depicted in Table 4. Incentives are categorized under Pleasure and Social factors. The [X] represents the incentives that are most likely to motivate/engage the particular demographic group. This was derived from an average of responses to corresponding pre- and post-survey questions from both user studies, where the possible response was a Yes/No/Maybe and the majority (in most cases, over 50%) of participants in that demographic group responded affirmatively to a given incentive factor. The absence of an [X] does not mean that a particular factor was not a motivator for a given demographic group. Rather, it simply means that this factor did not receive positive responses from the majority of people in that demographic group.

The mapping is based on results from the user studies. As such, it is limited to evaluating a subset of the motivational categories and incentives identified in Section 3.

Examining the intersection of Pleasure and Social factors with Age—the only demographic factor that produced statistically significant results—we see a number of relationships demonstrated in the table. First of all, under the Motivation category, Pleasure is a factor which is captured by the ability to Learn and the ability to contribute to Research. Contributing to Research is a motivator for both age groups, whereas Learning is not a factor that motivates many participants, regardless of Age. Moving to the Engagement category of this mapping, we see that Pleasure is again an

Table 4: Mapping of incentives to demographic groups

Motivator	MOTIVATION				ENGAGEMENT			
	PLEASURE		SOCIAL		PLEASURE		SOCIAL	
	Learning	To Contribute	Social Media	Competition	Learning	To Contribute	Social Media	Competition
	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gender								
Male	[X]	[X]			[X]	[X]		[X]
Female	[X]	[X]			[X]	[X]		[X]
Age								
U30		[X]				[X]	[X]	
30A		[X]			[X]	[X]		
Ethnicity								
White	[X]	[X]			[X]			[X]
Black		[X]			[X]	[X]	[X]	[X]
Other		[X]			[X]	[X]	[X]	[X]
Education								
Undergrad	[X]	[X]			[X]	[X]		[X]
Graduate		[X]			[X]	[X]	[X]	[X]

engaging incentive, as is Social. Under Pleasure, both age groups are kept engaged by Contributing to Research, but only participants under the age of 30 are also engaged by the ability to Learn. As for Social factors, participants under 30 are engaged by Social Media but not by Competition. Lastly, neither Social Media nor Competition is an incentive that engages the majority of the participants above the age of 30.

Age was the only demographic group that influenced motivation, and the remaining demographic groups were not found to be statistically significant predictors of motivation or engagement. This could be attributed to the limitations associated with the user studies discussed in the section 5.4. However, this table also shows other likely motivating and engaging incentives for other demographic groups, including Gender, Ethnicity, and Education.

5.6 Incentive Design Guidelines

Based on all the results highlighted in this mapping, we provide a number of general design guidelines for building a participatory sensing volunteering campaign, not just based on Age, but also on the other demographic groups.

- Use Pleasure incentives as a universal motivators: Regardless of age, desired participants should be motivated to join a campaign by the use of pleasure factors such as the desire to help the community or an opportunity to contribute to research. As suggested by the user studies, Contributing to Research appeals as a likely motivator to encourage participants to join a volunteer campaign, regardless of demographic affiliation. Learning, is an incentive that is likely to appeal to participants of either gender, as well as those who fall under White

ethnicity, or participants who happen to be undergraduate students. Therefore making the value of the campaign known, especially as it relates to research and learning new things, is an important aspect to motivating these kinds of users to join and participate.

- Use Pleasure incentives to sustain contribution of older participants (ages 30 and Above): Pleasure factors will also be effective incentives that engage these participants throughout the campaign. Contributing to Research and Learning are again the incentives of choice. Incorporating other Pleasure incentives such as Learning and Feedback will likely be effective in maintaining engagement for this age group.
- Use Social incentives to engage younger participants (under 30): Younger participants can be kept engaged through use of Social Media. Campaign organizers should also provide other social incentives such as recognition, competition and leaderboards to trigger engagement, see Section 2.3.2.3 for other social incentives.

5.7 Summary and Research Contributions

In Chapter 3, a survey was conducted to determine the influence of demographics on participants' response to both social motivation and pleasure as a motivator. Results of the survey showed that age influenced participants' responses to social motivation but had no effect on pleasure as a motivator. In this chapter, two user studies were conducted to validate the initial survey results and show transfer of findings to a different domain. User study results showed that age also had an influence on social

motivation but not on pleasure as a motivator in a real-world participatory sensing context, thus providing ground truth for the influence of age on the effectiveness of different incentives to motivate participants in participatory sensing campaigns. Similar results were found in both user studies. Using findings from the Foodie Frenzy and Watch it Bloom study, a mapping of incentives to the demographic groups for which they are likely to be effective was developed. Incentive design guidelines for participatory sensing campaign organizers to enable thoughtful selection of incentives for participatory sensing campaigns were also developed in this Chapter. The mapping and guidelines will be incorporated in the 4WT model to enhance the selection of incentives for participatory sensing campaigns. Next, I evaluate the applicability of the 4WT framework developed and discussed in Section 4.2 for the selection of incentives in participatory sensing.

CHAPTER 6: EVALUATION OF 4WT FRAMEWORK

In chapter 4, a framework (4WT) was developed to enable the thoughtful selection of incentives for participatory sensing. The framework considered the impact of user characteristics, application characteristics, and the usage lifecycle of participatory sensing applications on the effectiveness of incentives to motivate and engage volunteers in participatory sensing. Findings from the two studies in chapter 5 have shown that the 4WT framework has the potential to guide campaign organizers in choosing incentives that are effective for the target application and volunteer groups. In this chapter, I present an evaluation of the 4WT framework (Who, Why, What, When and Triggers) and show its applicability for both participatory sensing studies discussed in the previous chapter 5. Generalized incentive selection guidelines for participatory sensing are presented, as well as specific guidelines for the case of oil spills in the Niger Delta, discussed in Section 1.1.

6.1 4WT Applicability for Participatory Sensing

This section demonstrates how campaign organizers can apply the 4WT model by following a step by step approach to arrive at incentives that are likely to be effective for their specific campaigns. The Foodie Frenzy and Watch it Bloom studies are used as examples to show the applicability of the model to participatory sensing applications.

The user studies conducted clearly underlined the importance of understanding *WHO* the volunteer is in terms of their demographic context. In both the Foody Frenzy and Watch it Bloom studies, the target volunteers were faculty, staff and students recruited on a university campus where learning and research are prevalent. These benefits align with the interests of students (typically under age 30) and those with higher education. This understanding of the volunteers' demographic context was used to enhance recruitment for the user studies by providing a reason—*WHY*—that was relevant to the volunteers' context. Recruitment flyers explicitly highlighted contributing to research, learning, social media and competition as benefits of participating in the studies. This provided initial motivation before any kind of incentive mechanism was provided. See Table 4a.

In determining *WHAT* incentives would be provided, the mapping of incentives to motivators (see section 2.3.2.3) was considered, and corresponding incentives were selected for the studies based on the knowledge of *who* and *why*. Both study results showed that the most likely reason volunteers of any age or gender participated in the study was to contribute to research, indicating that the *why* was effective. *WHEN* highlights the two different phases of participation (a) motivation and (b) engagement, as well as the need to target incentives for these phases based on the campaign organizers knowledge of the user. In both studies, all age groups were initially motivated by the same reason, to contribute to research. However, each age group had a different reason for continuing to participate. For example, the motivation to conduct research related to phenology for Watch It Bloom and nutrition for Foodie Frenzy. Ages 30 and above were initially motivated by the desire to contribute to research

and they stayed engaged by the same factor over the three-week duration. Participants under 30, however, required an incentive different from their initial motivation to keep them engaged.

Lastly, for both studies, no reminders were provided over the three-week period. The number one feedback received from participants was the need for reminders. This emphasizes the need for *Triggers*.

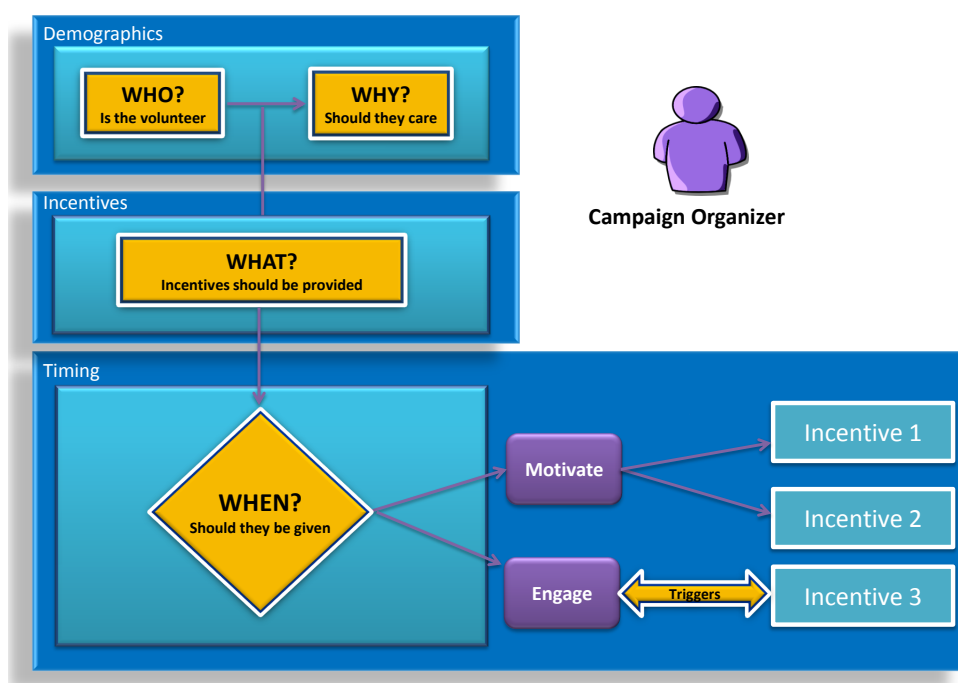


Figure 12: 4WT framework evaluation

In summary, using the 4WT framework, campaign organizers can begin to consider ways to optimize relevance and value based on the volunteers' context to set the stage for motivating participation before any kind of incentive is provided. Campaign organizers could use the 4WT framework as a guide to explicitly think about the benefits of their campaign and highlight the value of volunteer participation to increase understanding of the perception and implications of the task being performed. The

mapping of incentives to demographic groups developed and discussed in Chapter 3 could prove valuable as it provides campaign organizers with a clear reference to existing non-monetary incentives and their potential effectiveness for different volunteer age groups. Using 4WT, campaign organizers can plan for the use of these incentives to motivate the different phases of participation suggested by study results. 4WT is by no means a complete prescription of how to incentivize, but instead serves as a starting point for campaign organizers to consider the requirements of selecting incentives for participatory sensing campaigns and also as a building block for future studies on motivation and incentives in participatory sensing.

6.2 Application of 4WT to Motivate Volunteer Data Collection in the Niger Delta

Section 1.1 discussed a case of oil spills in the Niger Delta region of Nigeria and the potential for participatory sensing to foster a sense of citizen responsibility and corporate accountability towards reducing pollution in the region. Participatory sensing could be used to identify and report the leaks immediately as they occur so they can be repaired more quickly to reduce damage. Given the fact that oil spills occur both in remote villages, where the population is mostly elderly, and also in cities, which feature a more vibrant and youthful population, the following questions were asked: What incentives should be used? Will the incentive provided apply to both demographic groups? And if not, what specific incentives are more effective for each demographic group or the campaign as a whole? In this section, I apply the 4WT framework to arrive at guidelines for the application of participatory sensing to large scale reporting and data collection of oil pollution in the Niger Delta region of Nigeria.

6.2.1 Who is the Volunteer

Knowing your volunteers include understanding the demographic composition of volunteers as well as their environmental context. Niger Delta people live in very close knit communities, they are mostly farmers, fisher men and craftsmen who value nature, rivers, streams and agriculture, as these serves as their main source of livelihood and sustenance. However, these natural resources have been polluted for decades, causing the means of livelihood to diminish [68].

6.2.2 Why They Should Care

Volunteers need to be made aware of the intended outcomes for the campaign and the implications of their participation/or not in the campaign, as well as the possible benefits that could result from their participation. In our studies, the benefits of using the applications and the resulting outcome of the data contributed to the campaign was explicitly stated to the volunteers. For example, the Foodie Frenzy application asked participants to track their eating habits and participants were aware that the data collected would contribute to research on health and nutrition. In the case of the Niger Delta, the need for the campaign and the role of the volunteer in bringing about change and accountability should be emphasized. Benefits emphasized could include the fact that the use of technology serves as a peaceful and organized protest, which provides evidence of the destruction done to the communities and a way for the community to demand rights and privileges from the political processes in the country [68]. Benefits also include the potential for increased transparency on the path of the oil companies and government, which in turn leads to faster detection

and clean up of leaks. Given that the Niger Delta people are a close knit community, focus groups could be used to create awareness and bring about strong advocacy and a sense of comradery from the grass root.

6.2.3 What Incentives Will be Provided

Based on our study results, some motivators are better than others across all demographic groups, while some motivators are specifically more appealing to particular demographic groups. Therefore, incentives should be determined based on *Who* and an understanding of *Why*. The motivational factors of pleasure and pain, as well as social acceptance and rejection could be targeted for individuals in the Niger Delta. As we see from Table 4 in Section 5.5, motivational factors of pleasure and pain are the most likely to appeal to a broad collection of users. The pleasure and pain motivator is related to emotional pleasure or pain and the effect on attitudes, intentions, values or personal norms [11]. These individuals have over time experienced pain and bear the burden of perceived injustice and marginalization. All age groups are likely to be motivated to participate in a genuine effort to bring about change. Social acceptance and rejection, is related to the desire to belong to a stable framework of some ongoing relationship in which individuals share a mutual concern, while social rejection is a state in which individuals do not receive the benefits of inclusion [14]. The violence and restiveness in the area has been attributed to the feeling of alienation; the deprivation of a sense of ownership, and the notion that neither the oil companies nor the government care about their plight [68]. Following the survey and user study findings, social motivation should be targeted toward the youth. They are

likely to be motivated by the need for social acceptance; the feeling of being heard and the understanding that their struggles are no longer hidden from the world. This could be accomplished through social media. For the youth (volunteers under 30 years of age), social media tools such as Twitter, Facebook, Instagram and Youtube components should be integrated into the app to enable participants to share their content to these respective accounts to promote awareness, build reputation and social acceptance. For the elderly (volunteers above 30 years of age), the focus should be on collaboration, team work, community and comradary. Participants in this age range should be made aware of the value of their contributions and provided with regular feedback on the positive changes resulting from their participation.

6.2.4 When Should Incentives be Provided

As seen from the study findings, incentives should be targeted for different phases of participation: (a) motivation and (b) engagement. To target motivation, the pleasure and pain motivator could be targeted for all age groups. This involves emphasizing incentives such as the ability to bring about change in the society, ability to provide evidence of the damage done to the environment, ability to reclaim the communities' main sources of livelihood etc. To target engagement, the social acceptance and rejection motivator should be used, however, social incentives should be tailored to each of the individual groups as discussed above.

6.2.5 Triggers

Volunteers need support to remember the initial goal and maintain a consistent vision of the rewards of reaching that goal. Daily reminders to record data can be

triggered using the app. Other methods such as the use of regular focus groups, billboards and television and radio advertisements etc can be used as reminders.

6.3 Summary and Research Contributions

The 4WT framework presents an adaptive approach to motivating participatory sensing data collection campaigns for different contexts and user demographics. It provides generalized incentive solutions that can be tailored for a particular application and its collection of users. The potential for 4WT to enable campaign organizers to tailor motivation and arrive at incentives for large scale data collection campaigns has been demonstrated, and a step by step application of the framework for the case of oil spills in the Niger Delta has been outlined. The methodology used thus far derived the effectiveness of various incentives in motivating and engaging volunteers in a participatory sensing context. Furthermore, the developed framework produced a set of guidelines to motivate different application contexts and users types. Looking more broadly, the methodology and framework jointly serve as a road map for conducting research that further develops incentive selection guidelines for participatory sensing. The framework can be applied to study incentives for existing classes of applications, like participatory sensing for noise pollution, water pollution, disaster recovery etc. Other characteristics of users, applications and triggers within this framework can be further studied to develop additional design guidelines. This research also serves as the foundation for the design and development of adaptive incentive mechanisms that select the optimal incentive to encourage sustained participation. Variables defined as well as the incentives derived using the 4WT framework could serve as input param-

eters to derive a learned model, which will dynamically adapt incentive specifications in order to meet quantity and quality requirements. An example of the applicability of 4WT to such an approach is shown in Figure 13.

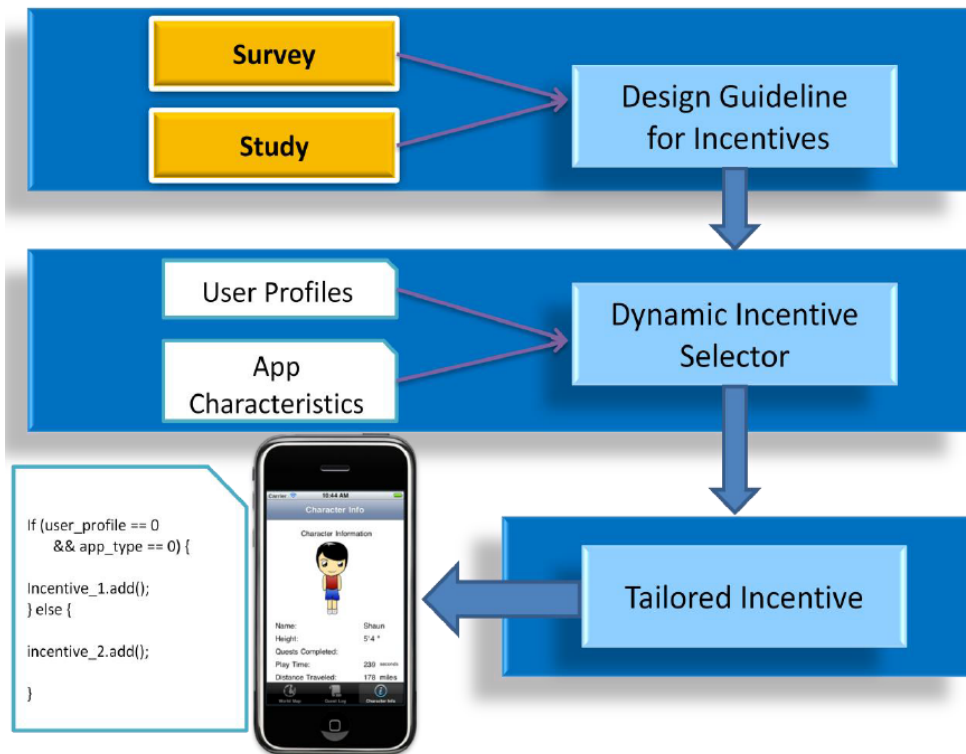


Figure 13: Application of 4WT for dynamic incentive selection

A limitation of this work, however, is that the user studies were not conducted in the Niger Delta region nor under the conditions of violence currently experienced there. Therefore, the specific results on the influence of age on incentive effectiveness cannot be generalized to the Niger Delta. Further research could be conducted on the influence of other demographic factors such as culture, socio-economic status and income level on the effectiveness of incentives. The effectiveness of other types of incentives for different age groups and other demographic groups could also be studied. Ultimately, this would lend itself to more effective incentive mechanisms for

motivating quantity and quality data contributions.

CHAPTER 7: CONCLUSION AND FUTURE WORK

The effect of motivation on volunteering is a topic that has been explored for decades. Recently, the importance of this subject has been carried into the field of participatory sensing and consequently, there has been a wide range of research conducted in this area. However, studies on motivation in the participatory sensing domain have yet to consider the impact of demographics on volunteer motivations. This work demonstrates the influence of age on the effectiveness of non-monetary incentives to motivate data collections in two different participatory sensing domains. The findings show that other demographic variables (gender, ethnicity and education) did not predict the effectiveness of incentives. To expand the impact of the study, other relevant demographic factors should be explored and a more representative sample used to study these issues in more depth.

The implication of this research is its potential to close the gap in the process of developing and selecting targeted incentives to motivate and encourage sustained volunteer participation in the field of participatory sensing. A major focus of this work was on the development of a framework to guide the selection of effective incentives that motivate large scale data collection campaigns in the participatory sensing domain. This framework was applied to provide an initial set of guidelines for motivating participatory sensing campaigns in ways that motivate initial participation and maintain continued participation through the duration of a campaign. The framework

is also applied to demonstrate how campaign organizers could potentially motivate data collection campaigns for the reporting of oil leakages in the Niger Delta region of Nigeria. The framework can be applied to study incentives for existing classes of applications, like participatory sensing for noise pollution, water pollution and disaster recovery etc. Other characteristics of users, applications and triggers within this framework can be studied to develop additional design guidelines. The application of this work to real-world problems can provide a foundation for meaningful research beyond my dissertation. Future work will explore the development of incentive mechanisms which enable dynamic, run-time selection of incentives tailored for individual volunteers in participatory sensing.

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APPENDIX A: DEMOGRAPHIC SURVEY

Incentive Survey

The following definitions are relevant for better understanding of the subject matter and survey content. Please take some time to read them.

Participatory Sensing: Leverages volunteers as data collectors using mobile phones. Participatory sensing volunteers use the sensors on their mobile phones to collect data (e.g. pictures, audio, and GPS/location traces) for specific research purposes (e.g. health, transportation and environmental issues).

Volunteering: The commitment of time to a task without formal monetary compensation

Motivation: The reason for performing a data collection activity

Engagement: Continuous participation in a data collection activity

Given the Participatory Sensing scenario provided below, please answer the next 3 questions

Imagine you were asked to download and use a phone application that maps your daily routes to display your exposure to air pollution. This application uses your phones GPS to upload your location traces to a secure server that will be analyzed by researchers. The information gathered helps you interpret the impact of your route choice for your health. The data collection process involves 2-3 weeks of constant monitoring to provide adequate feedback. You will be participating among others as part of a clean air campaign in your community.

1. How likely are the following to **motivate you** to participate in a data collection activity such as the one described above? *Please rate on a scale of 1 to 5, where 1 = Least Likely and 5 = Most Likely*

1. A chance to meet people and make friends	1	2	3	4	5
2. A chance to work as part of a team or community	1	2	3	4	5
3. A chance to build my reputation for volunteering over time	1	2	3	4	5
4. A chance to challenge myself or use my skills	1	2	3	4	5
5. A desire to help the community	1	2	3	4	5
6. Mere interest in the process of participating	1	2	3	4	5
7. A chance to learn about my exposure to emissions and how they relate to my actions	1	2	3	4	5
8. A chance to receive rewards	1	2	3	4	5
9. A chance to have fun while performing tasks	1	2	3	4	5
10. Other _____	1	2	3	4	5

2. How likely are the following to **keep you engaged** during a 2-3 week data collection process such as the one described above?

Please rate on a scale of 1 to 5, where 1= least likely and 5 = most likely

1. A data collection challenge/mission (e.g. like a competition with clearly established rules, and scoring) between participants	1	2	3	4	5
2. Clear unambiguous feedback for your contributions	1	2	3	4	5
3. Facebook wall posts about my contributions	1	2	3	4	5
4. Reward for my participation	1	2	3	4	5
5. Continuous learning experience from participating	1	2	3	4	5
6. Recognition (e.g. a certificate) for your contributions	1	2	3	4	5
7. Opportunities to be visible and socialize	1	2	3	4	5
8. If I enjoy participating	1	2	3	4	5
9. Constant reminders of the value of your contributions	1	2	3	4	5
10. Ability to work and collaborate as a team	1	2	3	4	5
11. Other _____	1	2	3	4	5

3. How likely are the following to **make you stop participating** during a 2-3 week data collection process such as the one described above?

Please rate on a scale of 1 to 5, where 1= least likely and 5 = most likely

1. If it does not give me the opportunity to socialize	1	2	3	4	5
2. If it becomes too challenging/competitive	1	2	3	4	5
3. If it becomes more about the reward than the good of participating	1	2	3	4	5
4. If I lose interest in the cause	1	2	3	4	5
5. If there is no recognition or acknowledgement of my contribution	1	2	3	4	5
6. If I stop learning new things	1	2	3	4	5
7. If participating is no longer fun and enjoyable	1	2	3	4	5
8. Other _____	1	2	3	4	5

4. Imagine you were asked to be part of a participatory sensing campaign to support volunteer monitoring of water quality in your community. You will be required to use your phone to provide photos and comments that capture information (e.g., the presence and color of algae in the water) about the watershed. This application requires you to deviate from your normal routine to visit the watershed.

Assume that you do not have a personal appeal towards the cause. Would you participate in a data collection activity such as the one described above?

- Yes
 No

5. Which of the following are potential reasons you would go out of your way to participate in the scenario described above?

(Please indicate how much you agree or disagree with the following)

1. I was asked to	1	2	3	4	5
2. It gives me a sense of civic duty	1	2	3	4	5
3. I like to be part of a team	1	2	3	4	5
4. I want to do something worthwhile	1	2	3	4	5
5. I want to socialize and build relationships	1	2	3	4	5
6. I want recognition for doing good things	1	2	3	4	5
7. I want prizes and rewards	1	2	3	4	5
8. I want to challenge myself	1	2	3	4	5
9. I want to feel accomplished	1	2	3	4	5
10. Other _____	1	2	3	4	5

6. What feature would potentially keep you engaged with a participatory sensing application?

(Please select the one that is most important to you)

- Text messages or pop ups on the screen to remind me to contribute data
 A leaderboard with my scores relative to that of other participants
 A point-based system that keeps track of the number of contributions I make
 A visual representation of my contributions (e.g. a map showing pollution levels along my daily routes)
 Facebook or Twitter feature so that I can share my contributions with friends and family
 Ability to invite friends to participate as a group

7. Assuming you have to deviate from your normal routine to contribute to a Participatory Sensing campaign, what incentive would you like to receive?

Technical

8. Which of the following functions is your phone capable of performing? *(Check all that apply)*
- Downloading applications
 - Taking and uploading pictures
 - Recording and uploading videos
 - Receiving GPS/location tracking
 - Browsing the internet
 - I do not have a phone
 - None of the above
9. Under which of the following circumstances would you consider using your mobile phone to collect data? *(Check all that apply)*
- If it easy and convenient
 - If doesn't drain my battery
 - If it doesn't interfere with my regular phone use
 - If it doesn't cost me anything
 - If it doesn't cost me too much

Demographics

We want to be able to compare motivation for volunteers of different ages and backgrounds so that we can better meet the needs of volunteers for these types of data collection activities. The next six questions help us do so. *(Please check only one for each).*

11. I am:

- Female Male

12. Which of the following age groups, represent your age?

- Under 20
- 20- 29
- 30 – 39
- 40 – 49
- 50 – 59
- 60 +

13. I am:

White

Black

Native American

Hispanic

Asian

Other _____

14. The highest degree or level of school I have completed is:

(If currently enrolled, mark the previous grade or highest degree received)

No schooling

12th grade or less

High school graduate (e.g. GED)

1 or more years of college, no degree

Bachelor's degree (e.g. BA, BS)

Master's degree (e.g. MS, MBA)

Professional degree (e.g. MD, LLB, JD)

Doctoral degree (e.g. PhD)

APPENDIX B: FOODIE FRENZY PRE SURVEY

Foodie Frenzy Pre-Survey

Page One

1. Do you like to eat? *

- Yes
 No
 Maybe

2. Why did you choose to download the Foodie Frenzy app? *

	Yes	No	Maybe
To earn points and compete for the leader board *	<input type="radio"/> Yes	<input type="radio"/> No	<input type="radio"/> Maybe
I was asked to participate *	<input type="radio"/> Yes	<input type="radio"/> No	<input type="radio"/> Maybe
To contribute to research *	<input type="radio"/> Yes	<input type="radio"/> No	<input type="radio"/> Maybe
To share my daily food photos on social media *	<input type="radio"/> Yes	<input type="radio"/> No	<input type="radio"/> Maybe
To learn about my daily food choices *	<input type="radio"/> Yes	<input type="radio"/> No	<input type="radio"/> Maybe

3. What do you look forward to while using the app? *

- Earning points and competing for the Leaderboard
 Helping out the research community by taking pictures
 Fun while capturing my daily nutrition
 Learning about my daily food choices
 Sharing food images and engaging on social media

Demographic Info

4. How old are you? *

5. Please select your education level? *

- Some college, no degree
- Bachelor's degree
- Master's degree
- Professional degree
- PhD

6. What is your Race? *

- Asian/Pacific Islander
- Black/African-American
- Caucasian
- Hispanic
- Native American/Alaska Native
- Other

7. What is your Gender? *

- Male
- Female
- Other

8. Which describes you? *

- Student
- Non Student

9. Please enter the same email you used to set up your Foodie Frenzy account *

APPENDIX C: FOODIE FRENZY POST SURVEY

Foodie Frenzy Post-Survey

Page One

1. Why are you still using the Foodie Frenzy app?

	Yes	No	Maybe
I can learning about my daily nutrition *	<input type="radio"/> Yes	<input type="radio"/> No	<input type="radio"/> Maybe
I can share my food images and engage on social media *	<input type="radio"/> Yes	<input type="radio"/> No	<input type="radio"/> Maybe
I can earn points and compete for the leaderboard *	<input type="radio"/> Yes	<input type="radio"/> No	<input type="radio"/> Maybe
I can contribute to research *	<input type="radio"/> Yes	<input type="radio"/> No	<input type="radio"/> Maybe
I enjoy capturing my daily food intake *	<input type="radio"/> Yes	<input type="radio"/> No	<input type="radio"/> Maybe

2. Please rank the features you enjoyed most while using the Foodie Frenzy App *

	Most Engaging	Engaging	No Effect	Not Engaging	Least Engaging
<input type="checkbox"/> Twitter	<input type="radio"/> Most Engaging	<input type="radio"/> Engaging	<input type="radio"/> No Effect	<input type="radio"/> Not Engaging	<input type="radio"/> Least Engaging
<input type="checkbox"/> Leaderboard	<input type="radio"/> Most Engaging	<input type="radio"/> Engaging	<input type="radio"/> No Effect	<input type="radio"/> Not Engaging	<input type="radio"/> Least Engaging
<input type="checkbox"/> Learning	<input type="radio"/> Most Engaging	<input type="radio"/> Engaging	<input type="radio"/> No Effect	<input type="radio"/> Not Engaging	<input type="radio"/> Least Engaging
<input type="checkbox"/> Points	<input type="radio"/> Most Engaging	<input type="radio"/> Engaging	<input type="radio"/> No Effect	<input type="radio"/> Not Engaging	<input type="radio"/> Least Engaging
<input type="checkbox"/> Facebook	<input type="radio"/> Most Engaging	<input type="radio"/> Engaging	<input type="radio"/> No Effect	<input type="radio"/> Not Engaging	<input type="radio"/> Least Engaging

Comments

3. Please enter the same email you used to set up your Foodie Frenzy account *

APPENDIX D: WATCH IT BLOOM PRE SURVEY

Watch it Bloom Pre-Survey

Page One

1. Do you like plants? *

- Yes
- No
- Maybe

2. Why did you choose to download the Watch it Bloom app? *

	Yes	No	Maybe
To learn about plants and climate change *	<input type="radio"/> Yes	<input type="radio"/> No	<input type="radio"/> Maybe
To share plant photos and engage on social media *	<input type="radio"/> Yes	<input type="radio"/> No	<input type="radio"/> Maybe
To earn points and be on the leader board *	<input type="radio"/> Yes	<input type="radio"/> No	<input type="radio"/> Maybe
I was asked to participate *	<input type="radio"/> Yes	<input type="radio"/> No	<input type="radio"/> Maybe
To contribute to research *	<input type="radio"/> Yes	<input type="radio"/> No	<input type="radio"/> Maybe

3. What do you look forward to while using the app? *

- Learning about plants and climate change
- Helping out the research community
- Fun while capturing plant images
- Earning points and competing for the Leaderboard
- Sharing images and engaging on social media

Demographic Info

4. How old are you? *

5. Please select your education level? *

- Some college, no degree
- Bachelor's degree
- Master's degree
- Professional degree
- PhD

6. What is your Race? *

- Asian/Pacific Islander
- Black/African-American
- Caucasian
- Hispanic
- Native American/Alaska Native
- Other

7. What is your Gender? *

- Male
- Female
- Other

8. Which describes you? *

- Student
- Non Student

9. Please enter the same email you used to set up your Watch it Bloom account *

APPENDIX E: WATCH IT BLOOM POST SURVEY

Watch it Bloom Post-Survey

Page One

1. Why are you still using the Watch it Bloom app?

	Yes	No	Maybe
I can learning about plants and climate change *	<input type="radio"/> Yes	<input type="radio"/> No	<input type="radio"/> Maybe
I can share my plant images and engage on social media *	<input type="radio"/> Yes	<input type="radio"/> No	<input type="radio"/> Maybe
I can earn points and compete *	<input type="radio"/> Yes	<input type="radio"/> No	<input type="radio"/> Maybe
I can contribute to research *	<input type="radio"/> Yes	<input type="radio"/> No	<input type="radio"/> Maybe
I enjoy capturing images of plants *	<input type="radio"/> Yes	<input type="radio"/> No	<input type="radio"/> Maybe

2. Please rank the features you enjoyed most while using the Watch it Bloom App *

	Most Engaging	Engaging	No Effect	Not Engaging	Least Engaging
<input type="checkbox"/> Points	<input type="radio"/> Most Engaging	<input type="radio"/> Engaging	<input type="radio"/> No Effect	<input type="radio"/> Not Engaging	<input type="radio"/> Least Engaging
<input type="checkbox"/> Leaderboard	<input type="radio"/> Most Engaging	<input type="radio"/> Engaging	<input type="radio"/> No Effect	<input type="radio"/> Not Engaging	<input type="radio"/> Least Engaging
<input type="checkbox"/> Facebook	<input type="radio"/> Most Engaging	<input type="radio"/> Engaging	<input type="radio"/> No Effect	<input type="radio"/> Not Engaging	<input type="radio"/> Least Engaging
<input type="checkbox"/> Learning	<input type="radio"/> Most Engaging	<input type="radio"/> Engaging	<input type="radio"/> No Effect	<input type="radio"/> Not Engaging	<input type="radio"/> Least Engaging
<input type="checkbox"/> Twitter	<input type="radio"/> Most Engaging	<input type="radio"/> Engaging	<input type="radio"/> No Effect	<input type="radio"/> Not Engaging	<input type="radio"/> Least Engaging

Comments

3. Please enter the same email you used to set up your Watch it Bloom account *

APPENDIX F: FOODIE FRENZY RECRUITMENT FLYER

Foodie Frenzy App





Scan QR code to download
or visit: <http://goo.gl/RxHgdT>

LEARN  SHARE  COMPETE  




When installing, go to Settings and enable installation of apps from sources other than Android Play Store


Contact:
Osa Omokaro
oomokaro@uncc.edu

This app is part of a research study conducted by Dr Jamie Payton and her PhD student Osa Omokaro to understand the effects of incentives on Participatory Sensing applications. Your contribution to this study is very valuable to us. Thank you for participating.


APPENDIX G: WATCH IT BLOOM RECRUITMENT FLYER

CAPTURE A PLANT EVERYDAY FOR 2 WEEKS

LEARN  SHARE  COMPETE 

WATCH IT BLOOM 

SCAN THE QR CODE TO DOWNLOAD THE APP
OR VISIT: <http://goo.gl/F6Hxsn>

 When installing, go to Settings and enable installation of apps from sources other than Android Play Store

Contact:
Osa Omokaro
oomokaro@uncc.edu

This app is part of a research study conducted by Dr Jamie Payton and her PhD student Osa Omokaro to understand the effects of incentives on Participatory Sensing applications. Your contribution to this study is very valuable to us. Thank you for participating.