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A THEORETICAL FRAMEWORK OF DATA QUALITY IN PARTICIPATORY SENSING: A CASE OF MHEALTH

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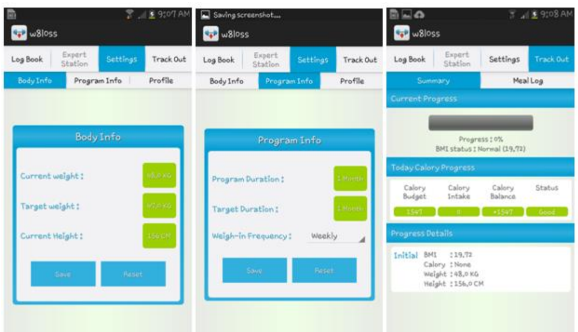
Graphical abstract



Abstract

Research in data quality is important in participatory sensing area to provide integrity of the data contributed by participants in mHealth participatory campaign. Many factors can influence the integrity of data contribution. One of major concerns is the possibility of data truthfulness of being uncertain due to incompleteness, imprecision, vagueness, and fragmentary. In participatory sensing, the interpretation of data quality is rather loose and there is no established theoretical framework that represents the elements of data quality in mHealth participatory sensing system. Therefore, the objective of this paper is two-fold: First, to investigate the variables of data quality that suits participatory sensing system. Second to propose a theoretical framework of data quality in mHealth participatory sensing. The finding will serve a guideline of data quality in mhealth participatory sensing.

Keywords: Data quality, information uncertainty, participatory sensing, mHealth

1.0 INTRODUCTION

The growth of smartphone era makes a new paradigm that smartphone is not only a device but capable of capturing moments as data through images, video recordings, audio, and *gps* information. Mobile phones becomes one of the important thing in human life, in which people carry mobile phones anywhere, and anytime. With large number of mobile phone users, it increases the capabilities of the device to capture, classifying or transmitting image, acoustic, location and others data in interactive or autonomous manner[6].

Mobile crowd-sensing is a mega paradigm of using mobile devices as a sensor to collect data, in which ***participatory sensing*** is included. Participatory sensing has unique characteristics that differentiate them from traditional sensor network. Participatory sensing is an approach of mobile crowd-sensing where citizens contribute data on participatory sensing platform and later may distribute the collected data, analyze and interpret them. In participatory sensing, human voluntarily act as sensors where people can perform data contribution alone or in group, and shares information about their life, habits, routines and enviroment that is captured by their mobile devices to improve quality of life.

In the recent years, participatory sensing system has been used as a mean for data collections in various domains like healthcare, cultural and heritage, urban planning, environmental monitoring system, and emergency response [1]. Many participatory sensing systems have been built to elaborate this paradigm to collect various scale of data using participatory sensing. The essential components of implementing participatory sensing system are capturing ubiquitous data, and leveraging data processing to enable the technical capabilities of these systems. These elements are especially important because it will offer mechanisms to support advocacy and civic engagement of participant in any participatory sensing campaign.

The aim of this paper is to propose a conceptual framework of data quality in participatory sensing that incorporate what is typically presented as information uncertainty in other computing domain as data quality in participatory sensing research area. We argue that in the view of participatory sensing literature, the interpretation of data quality is rather loose and there is no established framework that represents the elements of data quality in participatory sensing system. We will focus the argument of our study using a case of mHealth participatory sensing system.

This paper will serve a guideline of data quality in participatory sensing. This paper will explore on human factor or human error as the main factor of uncertainty information. To the best of our knowledge, this area is still very much unexplored. We will take a different direction with other researchers which mostly focus on improving the network or the system itself before sharing time process in the participatory sensing system. Furthermore, this paper will address the following research question; *what variables and factors of uncertainty information that might exist in participatory sensing system?* To answer this question, we have studied about the uncertainty information in a few domains and explore variables and factors that exists in each domain.

The rest of this paper is organized as follow: First, we give an overview about participatory sensing system. Second, we highlights the problem on data quality in participatory sensing system and how uncertainty information affect data quality. Third, we give an overview about the studies of uncertainty information in various domain and then specifically to the participatory sensing system. Next, we provide the discussion of our proposed framework for data quality in mHealth participatory sensing and last, we explain about our future works in this area.

2.0 DATA QUALITY IN PARTICIPATORY SENSING SYSTEM

2.1 Overview of Data Quality

Data quality is a combination of reliability, accuracy, completeness, timeliness, accessibility, consistency and validity of data [28]. In his study, Even *et al.* (2009) has stated the important of data quality in information system as higher quality of data makes the organizational data sources become more usable and consequently increase the benefits gained from the data [11]. This will contribute to the effectiveness and efficiency of business operation which also increase trust in information system [9]. In 2012, McNaull described the importance of data quality, where a low quality of data may results in incorrect contextual knowledge to be processed. McNaull argues that low quality of data in information system signifies a failure in anticipating user's need, where user may not being able to provide worthwhile interaction and not being able to adapt to any changes that may occur in the environment [20].

2.2 Data Quality in Participatory Sensing

Data quality is an important part of almost of all research area, including participatory sensing. Participatory sensing is an approach to distribute the data collection gathered from participant that giving contribution to the system in various aspects of their life. With a large amount of various data from many aspects, participatory sensing also have an aim to analyze and interpret the contribution data into something that usable to help improving life or environment. Participatory sensing networks will enable public and professionals to gather and share local knowledge of their life and the environment [6].

It is important to note that in most participatory sensing literature [13], they address three (3) main problems associated with the area. Anawar and Yahya (2013) classify the problems as incentive, identity, and integrity [2]:

a. Incentive: The motivator that drives the campaign participants in contributing data.
b. Identity: Level of anonymity and privacy of the campaign participants.
c. Integrity: The validity of the data contributed by the campaign participants.

We narrow down on the integrity aspect as our main concern, where participatory system has a unique set of issues associated with them. Ganti *et al*. (2011) said maintaining the integrity of collected sensor data is an important problem [12]. An idea called "human as sensor" become the foundation of participatory sensing system and it is not new, and have been applied successfully in personal sensing application for social improvement and health monitoring. Participatory sensing helps to collect a very large amount of data at various area. There is no doubt that gaining masses of information through participatory sensing in different domains is possible. Participants are expected to give and get correct and valid information where providers have the important role to provide the trustworthy information for users. In participatory sensing, participant is not only a contributor but also act as an information provider. Information gathered from the participant is hard to manage, because it involves a massive amount of data [28].

In a participatory sensing system, the validity of the collected data is highly depends on the sensing data collected by mobile devices carried by participants. Participants are expected to explicitly follow task guideline where instructions were given as to the duration of each activity needed and the manner of each activity to be performed. However, it is difficult for the system to obtain accurate sensing data, because high mobility and environmental complexity in participatory sensing systems may bring much more uncertainty, and there may be some inexperienced and non-reputable participants who will generate corrupted data [29]. This problem will greatly reduce the quality of the sensing result. Consequently, it highly important to improve the quality of the sensing data by identifying the information that has become uncertain due to the above problems.

Little attention has been given by researchers in participatory sensing area on how having human to operate, carry and interact with participatory sensing system affects participation, data quality and spatial-temporal coverage. Focuses on methods to model sensing of individuals, access their spatial and temporal availability and also determine the ideal feedback mechanisms will greatly help the data collection process. Having human as participant of sensing process leads to unique research challenge such like; can we model the "human factors" involved in the sensing process and use it to gather higher quality data while helping the users to have better understanding of their contribution [24].

While different explanation extend our understanding of data quality, inconsistent conceptualizations of the term can lead to confusion in identifying the elements of data quality in participatory sensing. In line with Reddy's work (2007), we strongly argue that human factor is one of the biggest influence to participant's contribution and some of participant's behavior leads to *uncertainty information* which in the end affects quality of data. Therefore, in the context of our study, we define data in participatory sensing is of high quality when:

> "Participant's contribution of sensed data is complete, accurate, up to date, and relevant within the context of the system and service provider's goal, while minimizing the uncertainty information"

Based on that definition, we propose hypothesis that if the contributed information having one of the elements of uncertainty then we could called it as uncertainty information which exists in participatory sensing system.

3.0 OVERVIEW OF UNCERTAINTY INFORMATION

3.1 Uncertainty Information

Data correctness issue and quality of data is important to be preconcerted before analyzing information. Information should be of high integrity when requirements of participatory sensing system is fulfilled. Unfortunately, the information shared by participants has possibilities of being uncertainty due to the user action toward the system. For example, information may not be clear, having vague meaning, some data is missing or it is not consistent. Uncertainty information is an existing issue in many research fields, including participatory sensing system. Those possibilities of uncertainty information bring us to untrusted information.

Kiurehgian *et al.* (2008), has classified uncertainty information into two (2) : aleatory uncertainty and epistemic uncertainty. *Aleatory uncertainty* is uncertainty that presumed to be an intrinsic randomness of some phenomenon, which means the uncertainty is being affected by nature and physical world [15]. On the other hand, *epistemic uncertainty* comes from a lack of knowledge or data. Uncertainty information is complex problem and affects decision making of service provider in participatory sensing system. The trustworthiness of information is in question because the information will later be used for life improvement. In order to handle the uncertainty information, it is necessary to study about the characteristics and factors that cause uncertainty information.

Berztiss (2002) studied about uncertainty management and explained various aspects of uncertainty which are inconsistency, vagueness, imprecision, incompleteness and rounding [5]. Among five (5) aspects of uncertainty, Berztiss highlight inconsistency as the variable to be measured. In 2004, Antifakos *et al.* introduced task difficulty, cost, knowledge of uncertainty, and level of uncertainty as variables in their work [3]. In 2008, Coppi defined various sources of uncertainty information which are randomness, imprecision, and vagueness. However, only imprecision and vagueness were used in his work. [7].

In 2012, MacEachren *et al.* explained the types of uncertainty to the components of information as: accuracy, precision, completeness, consistency, currency timing and interrelatedness or it has the same meaning as relevance [19]. In their study, MacEachren *et al.* used accuracy, precision and currency as variables they used. 1 year later, Dragos defined various types of uncertainty as precision, ambiguty, vagueness, and inconsistencies [8]. In the same year, Li *et al.* (2013) further explored the concept of randomness by categorizing unknowing exact result of event as randomness in uncertainty information [17].

From the literatures of uncertainty information, we found many variables that each research area may have different element(s) of uncertainty information and different technique(s) to solve uncertainty information. Some research may have more than one variable of uncertainty information to be tackled. We represents the variables of uncertainty information from various research areas in Table 1.

Table 1 Comparison of Uncertainty Elements

No.	Variable of Uncertainty	Studies	Explication	Participant Action
[1]	Incompleteness	[5], [18]	Missing data or information, information thorough	Participant should input every day in the morning, in the afternoon and night, but the information inputed is only in the morning and night.
[2]	Vagueness	[7], [8], [22]	The statement or the term is have unclear meaning or not specific	Middle-age men is young. Word "young" is not explain the specific age.
[3]	Inaccuracy	[19]	The measurement does not match to actual value.	The real number is 50.8 but written as 50.
[4]	Consistency	[5], [8]	Information comes from the same source but different information which shared or the same information shared from the different source.	A person shares information into a system that he/she walks to office but the distance is different
[5]	Level of UC	[3]	Various quality of the tips.	Participant found that the requirement is very clear or not really clear.
[6]	Imprecision	[7], [8], [19], [31]	The information is not fully real	The real weight is 50.8 but written as 50.
[7]	Randomness	[17]	Unpredictable action or unknowing exact result of event	A person inputing the information based on his/her mood.
[8]	Timeliness	[19]	Currency Timing	The actual time is not match with the receive time
[9]	Cost	[3]	Motivation of sharing information	Participant diligently contributing because of incentive.
[10]	Task Difficulty	[3]	Understanding level of task	Someone doing a homework but actually not fully understand of the homework.
[11]	Relevance	[21]	The information is related to each other or to guideline or the standart	BMI related to height and weight.
[12]	Knowledge of UC	[3]	Displaying the uncertainty	Participant understand that their act can give uncertain data/information.
[13]	Rounding	[3]	More like an estimation rather than the exact value	Participant entering their weight is 50 kg but it could be exactly 50 kg or 49,85 kg but rounded as 50 kg.
[14]	Ambiguity	[3]	Has two meaning or can be interpreted in two meaning.	User writing an information about themselves but the meaning is not clear and may leads to another meaning.

Based on comparison in Table 1, we develop uncertainty information taxonomy, to provide classification dimensions of possible variables corresponding to existing literature. As shown in Figure 1, the investigated variables are divided into three (3) categories:

1. Internal Effect: uncertainties comes from the nature of the information itself.
2. User Action: user action causes uncertainty information.
3. External Effect: uncertainties of information comes neither from the information itself nor from the person who share the information.

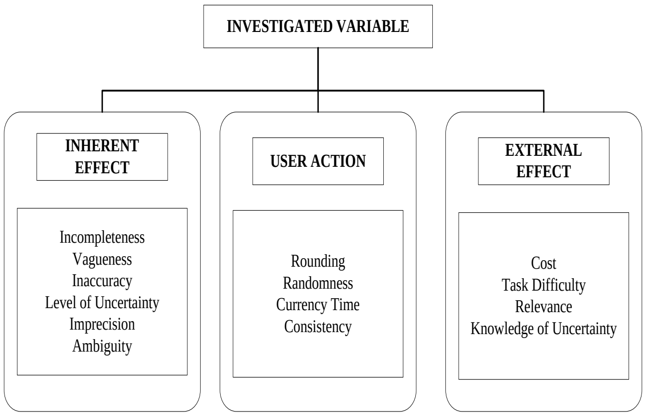


Figure 1 Uncertainty Information Taxonomy

3.2 Related Studies in Uncertainty Information

Liang *et al.* [7] studied uncertainty to developed a novel methodology of fuzzy inferenced decisionmaking (FIND) that solved the problem of decision making under uncertainty and incompleteness. They combined dual mode fuzzy belief state base and dual state fuzzy association as a new reasoning paradigm. FIND was tested in medical diagnosis application.

Relevance is a characteristic studied by Lalmas [16]. In the study, relevance is explained as a statement "of the less relevance is, the more uncertainty the information is". Lalmas studied relevance as characteristic in his work to constructed information retrieval model that aim to captured uncertainty as essensial feature of information but the result showed that the performance was not satisfactory. Relevance is also studied by Nottelmann *et al.* [21] using probability technique. They studied probability of relevances for advanced information retrieval application from uncertainty inference. of probability : linear function and logistic function. The result showed that the probability of relevances can be achieved but it was slightly improved by using logistic function. The same approach is taken by Wolf et. al [26], that solve relevance problem to handle uncertainty under incomplete database.

We represents our finding about the techniques has been used to tackle uncertainty information problem in various research areas in Table 2.

Table 2 Comparison of Related Studies

Studies	Uncertainty Element(s)	Technique(s)
[3]	Level of UC, Cost, Task Difficulties, Knowledge of UC	Probability
[5]	Incompleteness and Consistency	Bayesian Theory
[7]	Vagueness and Imprecision	Probability and Fuzzy Set
[8]	Ambiguity, Consistency, Vagueness and Imprecision	Semantic Analysis
[16]	Relevance	Evidence Theory
[18]	Incompleteness	Fuzzy Set
[19]	Inaccuracy, Currency Timing, and Imprecision	Statistical
[21]	Relevance	Probability
[22]	Vagueness	Bayesian Theory
[31]	Imprecision	Probability

4.0 UNCERTAINTY INFORMATION IN mHealth PARTICIPATORY SENSING

The phenomenon of using mobile phones as a sensor for human, increases the functionalities of devices and enable participants to contribute and share information ranging from their environment to their health state to improve their quality of life. mHealth participatory sensing system serve as data collection platform using mobile devices and allow community and stakeholder to collect, analyze and submit or share health information to a larger interactive participatory sensing network.

Many mHealth participatory sensing systems has been built to improve the quality of environment or for health care monitoring. mHealth participatory sensing systems will greatly reduce operational cost as it allows knowledge transfer between medical professionals and community, and improving community's participation in wellness care and health maintenance. mHealth participatory sensing systems will transform previously unmeasured behaviors and practices into personalized, evidence-based, in health-care domain.

There are difficulties in mHealth participatory sensing, one of the most challenging problem is to ensuring that the device is compatible and accessible and also to ensuring relevancy and accuracy of the data. To provide the patient with the most relevant data and help them with self-monitoring of their illness, it is better to sensing in frequency (Arvidson, 2012). There's also a lot of challenges in developing the infrastructure of mHealth participatory sensing systems and the main issue is to concern in knowledge representation from the information that gathered which is highly variable within different service providers and sources. The variability includes information uncertainty.

Yu *et al.* (2014) argue that research in participatory sensing area is still remains at theoretical and experimental stage. A system that enhances the quality of sensing data is required because data shared, captured, and collected by participants cannot be applied as intended if it is not reliable and inaccurate [29]. By having human as contributor of the sensing process will lead to a unique research challenge. Human factors has a big influence in elevating quality of data in participatory sensing because it will make the process of data gathering becomes more efficient and at the same time helping participants to understand more about their contributions [24]. Figure 2 shows stakeholders and architectural components of mHealth participatory sensing.

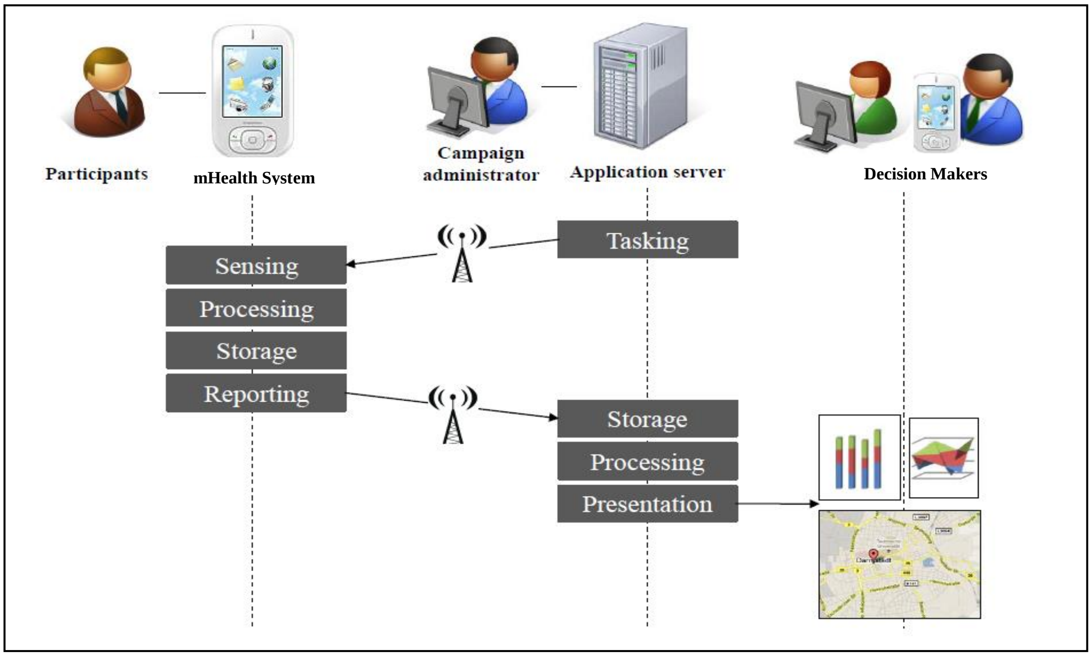


Figure 2 Stakeholders and architectural components of mHealth participatory sensing (adapted from Christin, D *et al*., 2011)

From literature, we found that there are rare studies being made concerning data quality in participatory sensing [24]. Presents quality involved in "human-in-the-loop" sampling with five variables in the metrics which are timeliness, capture, relevancy, coverage, and responsiveness. Timeliness presents the exactness of time of the event timing. Capture is a variable that affected by the sensor specifications and the capturing process by the participants. Relevancy is description of the phenomenon or event is corresponding to what that participant sense and it is can be completely irrelevant to completely relevant. Coverage is the representing of the spatial and temporal availability that associated with the coverage, and the key role of this variable are temporal extent and resolution. Reddy further describe responsiveness as the responding of the sensing request from the system by participants.

In 2011, [28] studied about improving data quality using reputation management in participatory sensing for data classification. They explored the trustworthiness of data or information from participants using reputation management approach and introduced three (3) categories of reputation: data quality record and participant's past performance (DR); participant's ability and device capabilities, represents personal information (PI); and, community trust and organizer trust, represents indirect reputation (IR). They came out with the conceptual classification model to classify data based on data trustworthiness level. Yang *et al.*, outlined that participant's ability was attributed to their responsiveness towards the system which is parallel with earlier argument by Reddy *et al*.

In 2013, [29] studied about improving data quality using their proposed accumulated reputation model in participatory sensing systems using Gompertz function and give a reputation score to contributed information [14] studied about a reputation system for mobile phone based sensing which focused on noise monitoring. They used robust average algorithm and combined it with Gompertz reputation and applied it in their module.

5.0 THEORETICAL FRAMEWORK OF DATA QUALITY IN mHEALTH PARTICIPATORY SENSING

5.1 Theoretical Framework

One of the interesting area of participatory sensing is in health-monitoring where participatory sensing helps people to monitor their health using their smartphones to maintaining or even improving their health. This is an interesting field to be explored in participatory sensing which the campaign should be in long-term time frames to collect the data and analyze it.

Due to the scope of this paper which emphasizes on participant's data input in M-Health domain, not all the variables will be used in the proposed data quality framework. From the presented literature, we found 14 variables that have been studied in data quality in various research areas, and 3 variables that have been studied particularly in participatory sensing area which is accuracy, timeliness, and relevancy. The data quality metrics that meets the nature of mHealth participatory sensing is accuracy, relevancy, completeness, and timeliness. .

This study focus on variable that can be affected by human errors as one of the factor that influencing the trustworthiness of data and cause uncertainty information. The variables chosen are variables that can cause the data become uncertain when it comes from participant contribution behavior. We exclude coverage as variable due to scope and limitation of this study which not focus on spatial and temporal areas because coverage and device's capability are mostly influence by the sensor or the device not human as contributor. Output of this study is to determine the reputation of participants of participatory sensing campaign based on their contribution data and level of uncertainty of their contribution based on the quality of data that they shared while using mHealth application.

We represents our finding about uncertainty elements in participatory sensing system that has been studied by other researchers in Table 3.

Table 3 Uncertainty Elements in Participatory Sensing Research(s)

Variable(s)	Author(s)		
	[24]	[28]	[29]
Timeliness	√	√	-
Accuracy	-	-	√
Relevancy	√	-	-
Completeness	-	√	-
Responsiveness	√	√	-
Capture	√	√	-
Coverage	√	-	-

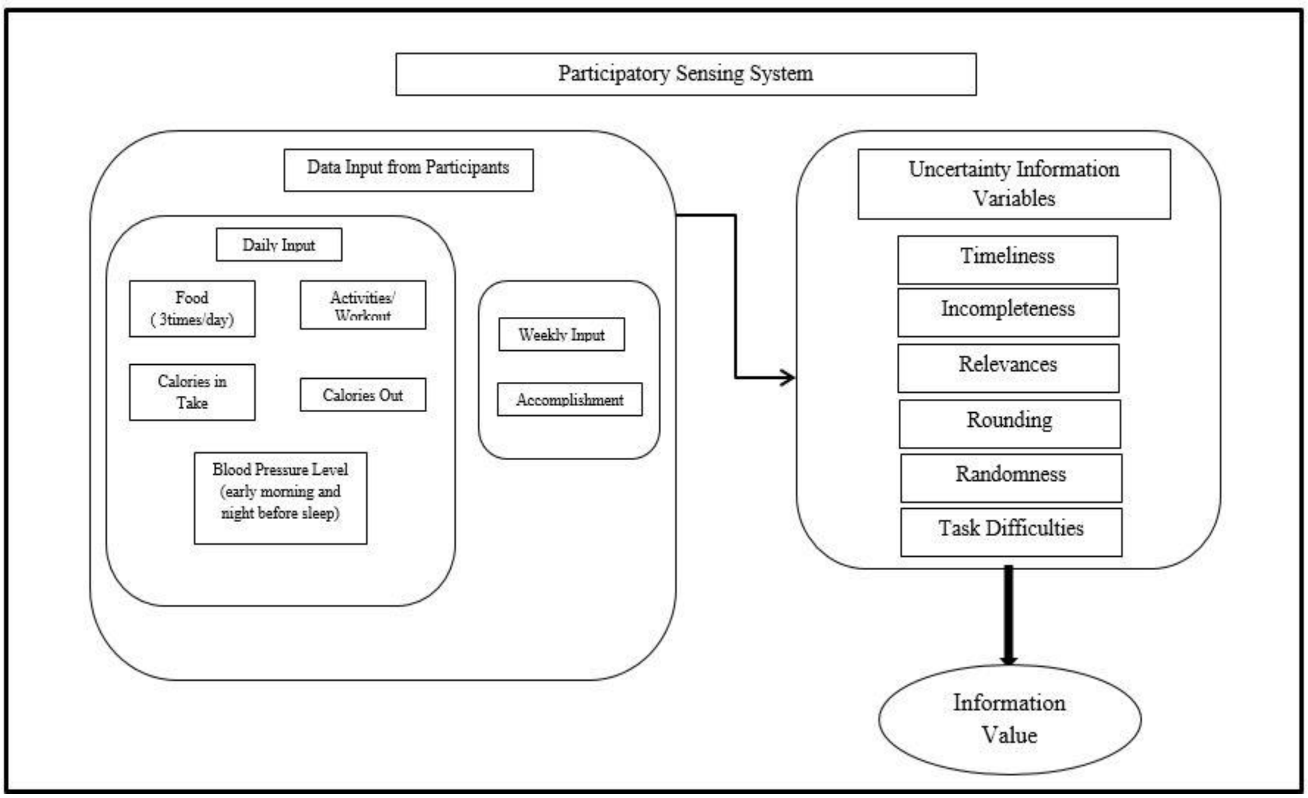


Figure 3 The Proposed Theoretical Framework for Data Quality in mHealth Participatory Sensing

Figure 3 shows the proposed theoretical framework for mHealth participatory sensing. We applied the experimentation variables set in [23] as the data to be examined in our framework. The experimentation variables are

a. Participant Input (t) = The quantity of participation is measured by the frequency of input recorded by the participants. The requirement was participant should record their weight for each week. The frequency is compared over weekly time intervals that make up the data collection periods. Only participants who input 2 or more in at least one month will accounted for data collection.

b. Targeted weight (O) = To accomplish the goal of the campaign, participant must record their target weight as a requirement to be analyzed whether the number is achievable or not.

c. Weight (W) = The variable calculated by the initial and final weight recorded. In the experiment the following formula will be used:

$$Weightloss = \frac{InitialWeight - FinalWeight}{FinalWeight}\ x\ 100 \quad (1)$$

d. Goal accomplishment (tg) = To have the quality of participation, the appropriates of goals was evaluated and the number of it served as the indicator for quality participation. Goals were considered appropriate if the targeted goal using guidelines. Then, the accomplishment rate for the goal is calculated. For goals variables, the data is coded using the following formula:

$$Goals = \begin{cases} \frac{Weightloss}{Initial\ Weight - Targeted\ Weight} & 1\ Goals > 1 \\ & 0\ Otherwise \end{cases} \quad (2)$$

e. Calorie (e) = Calorie is an important thing needed by human body to live. Calorie will be made to be energy in where calorie obtained from food but overage calorie in human body can cause diseases. Physical activity expends calorie as energy out. Increasing physical activities will increase calorie expended as well.

In Table 4, we present our proposed variables of uncertainty information for the framework based on elements of uncertainty information in literatures review. We introduces the attributes that affects each variables along with the perceptual of each attributes. In Table 5, we present the indicators that determine whether the attributes of uncertainty information exist during data collection process.

Table 4 Uncertainty Variables in Participatory Sensing Research(s) and Attribute(s) Perceptual

Variables	Attributes	Attributes Perceptual
Timeliness	Inconsistent	When the data is not continual
	Out-of-date	When the data is not following the timeframe
Incompletes	Missing Data	When the data is missing or not fulfilled properly
	Inactivity	When the data is represent laziness
	Data record	When the data records is out of number
Randomness	Assumption	When the data is based on presumption
	Uncorrelated	When the data is out of context
	Comprehension	When the user is not understand the task in and out
Rounding	Rounded	When the data is being rounded
	Estimated	When the data is size up
	Improper	When the data is not factual
Relevance	Goals	When the data is not meet the requirement which set as target by user
	In the range	When the data is out of boundaries of standard guideline
	Conform	When the data is not correspond to the requirement which set by user's target.
Task Difficulties	Task handling	When the user cannot perform well towards the system
	User availability	When user occupation affect to user performance toward the system

Table 5 Indicator(s) of Uncertainty Variables in Participatory Sensing Research(s)

Variables	Attributes	Indicators
Timeliness	Inconsistent	Sometimes/ not always
	Out-of-date	Actual time
Incompleteness	Missing data	Unfulfilled
	Inactivity	Laziness
	Data records	Deficient
Randomness	Assumption	Probably/maybe/about
	Uncorrelated	Carelessly
	Comprehension	Understood
Rounding	Rounded	Even number
	Estimated	Size up
	Improper	Not exact/ not detail
Relevancy	Goals	Achieve
	Range	Normal range
	Conform	Following
Task difficulties	Task handling	Hard
	User availability	busy

5.2 Work in Progress

We apply the proposed framework on our mHealth participatory sensing system called w8loss that is developed in Android platform. This system aims to help people to maintain or improve their quality of health by monitoring and controlling their food and their ideal calories in-take each day in terms of doing healthy diet and reduce weight periodically to suppress the chance of their obesity becomes others coroner disease.

Data from this system will be collected in web databases. The application has food database, workout option, calculation of BMI and calculation of calories budget of each day based on participant's BMI information. We include some of screen captures of the application.

As shown in Figure 4, we include some of screen captures of the application.

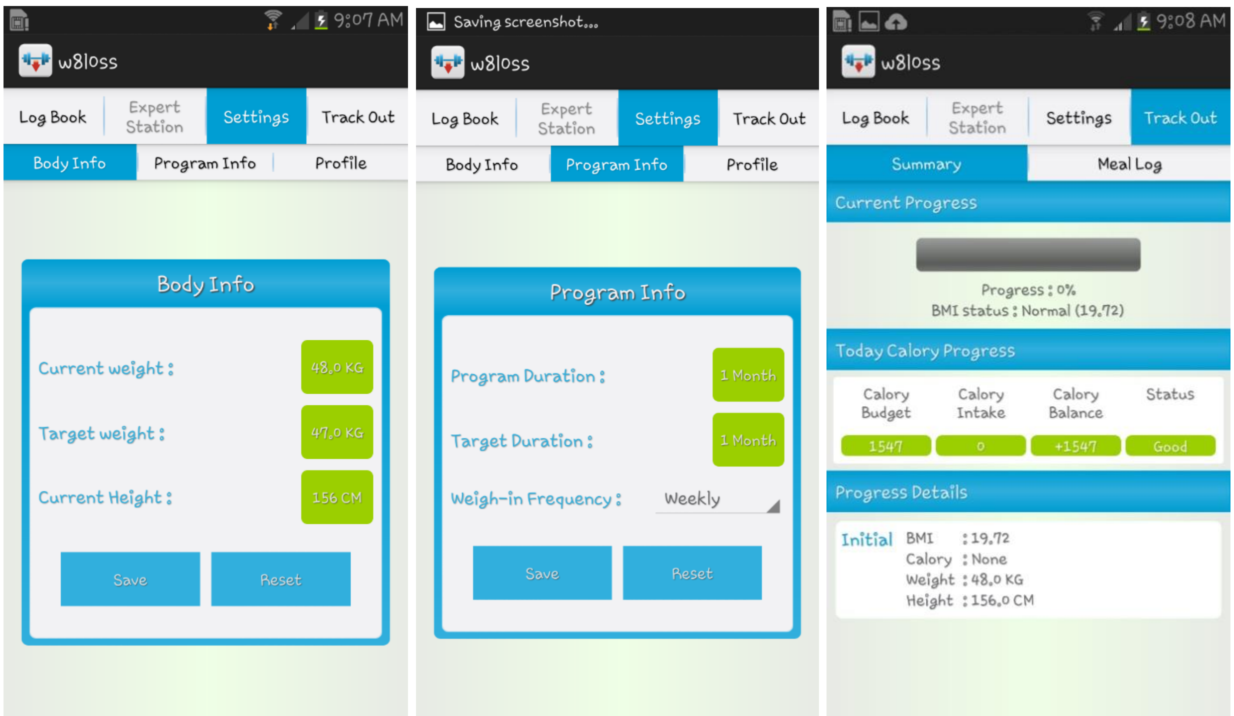


Figure 4 W8loss application screen captures

6.0 CONCLUSION AND FUTURE WORK

In this paper, we identify variables and factors of uncertainty information that might exist in participatory sensing system by providing uncertainty information in a few domains and explore variables and factors that exists in each domain. Next, we propose a conceptual framework of data quality in participatory sensing that incorporate what is typically presented as information uncertainty in other computing domain as data quality in participatory sensing research area. The six (6) variables included in the proposed framework are Timeliness, Incompleteness, Randomness, Rounding, and Relevancy.

For future work, we will perform data collection and analysis using a qualitative Data will be collected through interview with each participant as respondent after they have using the w8loss application for two (2) weeks. The collected data will be analyze using Atlas.ti, a qualitative data analysis software for qualitative research. The finding will be validated using the statistical validation on the data collected in mHealth database.

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