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A Design Guideline for Non-Monetary Incentive Mechanics in Mobile Health Participatory Sensing System

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Abstract

Participatory sensing emphasizes the participation of citizens and community groups in the process of sensing and documenting current events in their local environment using smart phones and mobile devices. Incentive is crucial in participatory sensing data collection to attract participants to join in a participatory campaign, and to engage participants to use the participatory sensing application. The challenge in studies on non-monetary incentives is how this type of incentives should be represented in a participatory sensing system because they are inherent to the participants. This study proposes a design guideline which consists of set of mechanics and features associated with each incentive construct based on Self-determination Theory and Motivation 3.0. The design guideline is presented in a hierarchical system structure to illustrate dynamic operation of incentive mechanics with different components in participatory sensing system. Content analysis is performed on 283 mobile health monitoring application in the market to determine the reliability of the proposed incentive mechanic and features through descriptive analysis and inter-coder reliability analysis. The findings of the descriptive analysis show that a relatively small proportion of the mobile application (15 percent), addressed at least one feature that tapped on each of the incentive mechanics, and almost all apps contain a minimum of one intrinsic incentive mechanic feature. The findings obtained from inter-coder reliability analysis found 56 percent of the proposed incentive mechanic features with low reliability. Furthermore, the finding shows insignificant reliability degree for almost all extrinsic features. This study provides both theoretical, and practical contributions. On the theoretical aspect, this study provides validation on the incentive mechanics and their features that have been proposed in the design guideline. On the practical aspect, the design guideline may aid system developers and service providers to implement the incentive concepts into systems' features and further help campaign organizers and service providers to focus on the best incentives strategy for improving participants' performance in the next participant recruitment.

Keywords: Participatory Sensing, Incentive, Mobile Health Monitoring, Self-determination Theory, Content Analysis

INTRODUCTION

Participatory sensing data collection is a data gathering process which involves research participants or community to collect and perform a task specified by campaign organizers through smart phones and mobile devices[1]. In participatory sensing, incentives will be given to the participants to enhance participants' performance in data collection activities. There are two main types of incentive mechanisms namely monetary and non-monetary incentives. Monetary incentive involves financial or valuable rewards which include cash, coupons, points, and redeemable credits. Non-monetary incentives are the non-financial rewards which may be extrinsic and intrinsic to the participants.

The current participatory sensing literature has identified non-monetary incentives that can influence participants' performance in participatory sensing data collection and typically classified them into intrinsic or extrinsic incentives. However, we argue that in the view of participatory sensing literature, there is a lack of design guideline that outlines participatory sensing systems' features that represents the behavioral incentives constructs. While non-monetary incentives has been shown to affect participants' performance in data collection [2], however, they do not depict the actual features in participatory sensing system. To the extent of our knowledge, this area is still very much unexplored. Few research has been done on non-monetary incentives in participatory sensing because it creates a false impression that the practitioners cannot demonstrate this type of incentives. Particularly, it is difficult to demonstrate intrinsic incentive because they are inherent to the participants [2].

The aim of this paper is to propose a design guideline for non-monetary incentive that is typically presented as motivated behavior in the psychology literature onto incentive mechanics. Recognizing substantial challenge in incorporating behavioral incentive constructs into participatory sensing system design, this study attempts to propose a standardized incentive mechanics that could be utilized by system developers to demonstrate or measure non-monetary incentives. Identifying the incentive mechanics could establish significant milestones on how it could enable the participatory sensing system to conduct and report participants' performance summary in an automated and real-time manner.

The design guideline for incentive mechanics would help campaign organizers and service providers to focus on the best incentives strategy for improving participants' performance in the next participant recruitment.

The rest of this paper is organized as follows: The first part of the paper presents Self-Determination Theory (SDT) and Motivation 3.0 as the theoretical foundation for the proposed guideline. We then explain how the design guideline is constructed by mapping each dimension of the behavioral incentive constructs in the theoretical framework into incentive mechanics in participatory sensing system. The mapping of the incentive mechanics is presented in a form of hierarchical structure to demonstrate the dynamic operation of the proposed incentive mechanics with each component in the participatory sensing system, namely participant, system, and campaign organizer. Next, the data collection procedure to compile a list of apps for content analysis is presented. The apps are screened according to the exclusion and inclusion criteria in order to draw a sample for further assessment in content analysis. Finally, this study determines the reliability of the proposed design guideline by performing content analysis for each incentive mechanics onto the collected apps sample. Descriptive analysis and inter-coder reliability analysis are performed to find reliable incentive mechanics that contributed positively to participants' performance for future participatory sensing system.

INCENTIVES IN PARTICIPATORY SENSING

Smartphone sensors such as camera and GPS can be utilized in various ways to perform data collection activities such as providing a bicycle route in CycleSense project [3], capturing flora pictures in Budburst project [4], or scanning barcodes to compare items' prices in LiveCompare[5]. Gao et al. [6] has outlined incentive mechanisms as one of the main components in participatory sensing data collection to provide strategies for increasing participation and reputation to data contributors.

This study will focus on the incentive mechanism in participatory sensing data collection as the main interest. The most important aspect when explaining about incentive in participatory sensing data collection is to describe the reason why it is needed. In participatory sensing, incentive is a reward gain by a participant. Incentive is crucial to (1) recruit participants to join in a participatory campaign, and (2) to engage participants to use the participatory sensing application. Incentive is necessary in the participatory sensing system because participating in a campaign may incur monetary costs and resource usage [6] [7]. Therefore incentives are used to offset and encourage participants to tolerate these costs and make contributions [8]. Unlike traditional sensor networks where a sink node has the complete control of all sensors' behaviors, smart devices are rather personal, and only the owner can decide when, where and how to use it for participation. With regard to data contribution, incentive may influence participants' decision and increase quality of contributed data.

Non-monetary incentives can be categorized as being either intrinsic or extrinsic. Intrinsic means that the incentive is based on purely personal reasons and inherent to a person, such as self-enjoyment, satisfaction, pleasure, and self-achievement. For instance: creating something, learning something new, developing a skill, solving a problem. Extrinsic means the incentive is influenced or controlled by external regulation, or other people. Examples include: a promotion, recognition; and at the other end of the scale: loss of occupation, a punishment.

INCENTIVE MECHANICS DESIGN

This study integrates constructs from two prominent theories in motivational study: self-determination theory [9] and Motivation 3.0 [10] as a theoretical foundation for analysis, within the context of participants' performance in participatory sensing. The underlying theoretical foundation is discussed later in subsequent sections.

Self-determination Theory (SDT) and Motivation 3.0

Prior to this study, SDT has been applied to study user acceptance in crowdsourcing [2] and citizen science [11] research areas. In this study, the integration of the two theories is done according to the similar explanatory accounts [12] in explaining user behavior in behavioral research. Integration occurs when the basic constructs of the two theories are combined to produce a novel insight into an application to non-monetary incentives in the participatory sensing domain.

SDT [13] is particularly focused on physically and psychologically adopting healthy behaviors and maintaining them over time. Three critical factors in SDT are the sense of autonomy, competence, and relatedness. In short, the central importance of SDT in health is, a person will initiate and maintain their healthy behavior when they have the ability to make informed decision (autonomy), experience a confidence to change (competence) and feel connected to a global outcome (relatedness). Ryan et al. [14] further extended the SDT model to health behavior change. In the model, the participant's knowledge of autonomy, competence, and relatedness are affected by the treatment environment, by individual preferences, and by the intrinsic and extrinsic value of the participant's perception.
Motivation 3.0 [10] focuses on intrinsic motivation where the drive to perform a task is predominantly because it is interesting, challenging and absorbing. This theory is widely adopted in business and workplaces. Pink outlines three meaningful constructs: purpose, mastery and autonomy. In essence, Motivation 3.0 proposes that workers need some freedom in how they complete a task, need to be working on

tasks that consistently challenge them, and need to believe that the tasks they are doing serves a purpose beyond what is required.

Although SDT distinction between intrinsic and extrinsic incentives has served as the explanatory account in much work seeking to explain user behavior, Pink's [10] distinction between intrinsic and extrinsic incentives has been used in similar ways to SDT, which is particularly suited in a workplace. The dimensions of each construct are tailored and mapped based on the literature found on participatory sensing and behavioral studies. The following discussion will examine how these constructs could be applied to health behaviors, especially to mobile health monitoring behavior:

Autonomy: In participatory sensing, participants exhibit a sense of autonomy when they feel that they have the ability to make a decision over the direction of the assigned task. In this study, autonomy is characterized by the following: (1) Self-directed (2) Perceived choice (3) Goal setting.

Mastery: Mastery incentive mainly refers to the feeling of getting better at performing a task [10]. This study outlines four dimensions of how mastery improves participant performance at the assigned task: (1) Task enjoyment (2) Perceived competence (3) Challenge, and (4) Learning.

Purpose: Purpose construct in Motivation 3.0 is the desire to perform the assigned task for a certain cause. In purpose, satisfaction in performing data collection depends on having right goals that are valued and perceived as personally important, or for a greater cause which are larger than participants' self-interests. In this study, autonomy is characterized by the following: (1) Intrinsic goal (2) Personal value (3) Altruism.

Social: Deci and Ryan [9] explain that when a task is not inherently interesting and enjoyable, individuals will perform the task because they feel understood and connected to the people around them (family, peer, or group). Social connectedness would be formed and supported by: (1) Extrinsic goal (2) Cooperation (3) Competition (4) Recognition

Mapping Incentive Constructs into Incentive Mechanics

The challenge in investigating theory-driven non-monetary incentives in participatory sensing system is how to conceptualize the theoretical framework into an IT artifact. What has been relatively unexplored in existing studies, however, is how to demonstrate non-monetary incentives which were inherent to participants. This study perceives the importance of an IT artifact to provide a tangible research results in order to reach practitioners and stakeholders in the participatory sensing system. As an inter-disciplinary research, this study attempts to address knowledge void between behavioral study domain and participatory sensing domain by extending the psychological incentive construct into participatory sensing system, offering a better understanding on how an IT artifact can be used to incentivize participants in participatory sensing data collection. To conceptualize an abstract concept in the psychological domain, how participants engage and behave with various technological artifacts must become a central concern [15].

In the context of this study, the IT artifact is presented as a set of features in participatory sensing application that can be used as building blocks to incentivize participants during data collection activities. These features are called incentive mechanics. The incentive mechanics are derived by mapping the theoretical conception in the initial framework through various tools in an existing mobile health system. By designing a guideline for incentive mechanics, this study should be able to embed psychological presence to an IT artifact that constitutes this research despite quantitative and qualitative methodological adoption.

Based on the literature review, some studies have investigated the role of theory driven non-monetary incentive constructs in facilitating participants' performance in participatory sensing data collection. For instances, Omokaro[16] has developed a 4WT framework drawn from Fogg's behavior model, which provides a design guideline for participatory system developers on how to match participant's background with incentive type. On the other hand, Durst and Grottke[17] developed a model which adopts activity theory and Vygotsky's model of mediated act to illustrate the dynamic operation of the StreetSpotr system rather than depicting the non-monetary incentives. However, none of them propose a set of mechanics or features associated with non-monetary incentives for participatory sensing systems.

This study first mapped the previously defined incentive constructs into incentive mechanics. All incentives mechanics represent each dimension in the construct and correspond to mobile health participatory sensing setting in order to maintain coherency of this study. The incentives mechanics are mapped by reviewing relevant literature on application of Self-determination Theory in mobile application development and conducting discussion with two mobile apps developers. Table1 illustrates how four constructs in the study: autonomy, mastery, purpose, and social could be applied to mobile health participatory sensing setting. In the context of this study, autonomy mechanic is characterized by features that allow participants to demonstrate individual initiatives in terms of activities, goal, and perspectives. Mastery mechanic is characterized by features that allow participants to exhibit their skills, perceived ability, knowledge, and interest. Purpose mechanic is characterized by features that allow participants to demonstrate achievement, personal value, and contribution to the research outcome and community, while social mechanic is characterized by features that allow participants to relate with other participants and gain social support.

Table 1: Mapping of Incentive Constructs Into Incentive Mechanics

Construct	Dimension	Mechanics	Features Description
Autonomy	Self-direction	Self-monitoring	Allow continuous self-monitoring by recording information
			Information addressing purpose of user participation
		Plan and orders	Allow individual plan to lose weight
	Perceived Choice	Activities option	Offers at least more than one way to complete task
			Acknowledging individual perspective and user feedback
	Goal Setting	Goal setting	Provides user-defined target goal
Mastery	Task Enjoyment	Participant feedback	Allow user to express enjoyment and satisfaction of doing task
	Competence	Task progress	Cue to achievement or progress
	Challenge	Challenge and quest	Provides plan of action for reaching target goal
			Allow user to increase skills/ modify behavior
	Learning	Education tailored	Offers user-specific education tailored to a user's needs
			Provide basic educational materials
Purpose	Intrinsic and Extrinsic Goal	Goal achievement	Display intrinsic or extrinsic achievement
	Personal value	Personal Duty	Duty or obligation to satisfactorily perform or complete an assigned task.
	Altruism	Data exporter	Allow user to send data/info to service provider
			Allow user to contribute to the community
Social	Cooperation	Social Network	Allow user to communicate with other participant
		Friend finder	Allow user to find new friends
	Competition	Leader board	Allow users to compete with each other
	Recognition	Recognition	Offers reward as an objective is achieved
			Offers reward as participant is engaged/involved in activities
	Punishment	Penalty	User will have a consequent penalty for failure

Design Guideline for Incentive Mechanics

The dynamic operation of incentive mechanics and campaign performance is illustrated by the proposed design guideline for incentive mechanics. In the context of this study, the design will serve as a guideline to evaluate participants' performance in a mobile health participatory sensing campaign and aid service providers in creating and developing participatory sensing system. Mobile health is selected as domain of study due to the noticeable effect of non-monetary incentive in health monitoring campaigns which require ongoing commitments from participants [14].

A participatory sensing system must dynamically adapt participant behavior towards better quality experience. The participant, the system, and campaign organizer components are not only closely interconnected with each other, but the flow of the interaction between the components can be seen in a form of hierarchical structure, in which data interpretation of each layer is reflective to the next layer. The incentive constructs in the first layer are reflective to the incentive mechanics in the second layer, and the incentive mechanics in the second layer are linked to performance evaluation in the third layer. The hierarchical structure of the non-monetary incentive mechanics design in this study is shown in Figure 1.

METHODS

Although weight-loss apps are not strictly bounded by region, an app available in one country may not be available in other countries. Therefore, the analysis is limited to the apps available in Malaysia, which the researcher had access to. In order to draw a sample, apps in Google Play (Android) and the App Store (Apple) store is searched using the keywords of "weight loss" and "diet" in Malay and English languages.

Exclusion and Inclusion Criteria

Between 29 August and 10 October, 2016, a list of apps was compiled by examining the title and description of apps searched based on the keywords given. Apps are reviewed in two-phase evaluation. In the first phase, general exclusion and inclusion criteria were established to limit the scope of apps being evaluated. Furthermore, criteria used will provide clear guideline to ensure only relevant review is performed. Among the apps searched with keywords, apps review is excluded if it meets one or more of the following cases:

a. Apps that emphasizes on physical exercise and workout activities unless they clearly stated their purpose as weight loss apps.

b. Apps that were developed by a medical institution to aid medical treatment for obese patient, rather than for general consumers.

c. Apps that are distributed in non-overlapping marketplace.

Next, the general inclusion criteria of the weight loss apps were coded according to the guideline given [18] which is platform (Google Play, or App Store), price type (free or paid), developer type (individual, individual developer groups, non-profit organizations, or companies), content type (information-centric, function-centric, or information-function balanced), individual user rating, and apps rating. The inclusion criteria are outlined based on the requirement of participatory sensing application, which is intended for data collection for community or research purposes. Therefore, apps will be included into the second review phase if they meet all of the following cases:

a. Price type: free

b. Developer type: individual, individual developer groups, non-profit organizations

c. Content type: function-centric, or information-function balanced.

Data Sampling and Collection

Each app was reviewed by two undergraduate students who served as the coders. The coders were selected based on their involvement as respondents during face validity for survey instrument. Coders were provided with two separate training for each phase. In phase 1 training, coders were asked to review description given in each apps page based on the exclusion and inclusion criteria. Ten apps were picked randomly from each platform (Google Play and App Store) and assigned independently to each coder.

In phase 2 training, coders were asked to download apps from the initial sample in phase 1 that met the exclusion and inclusion criteria. For each app, coders went through all initial construct assessment provided by the researcher and assigned values for each feature using binary system. Each app was assigned a '1' to signify the presence of particular feature in the construct, or a '0' to signify the absence. After the training was done, inter-coder reliability was calculated manually based on the guideline by Lombard, Synder-Duchand Bracken [19]. The results were discussed between coders and the researcher before the coders proceeded on the actual content analysis.

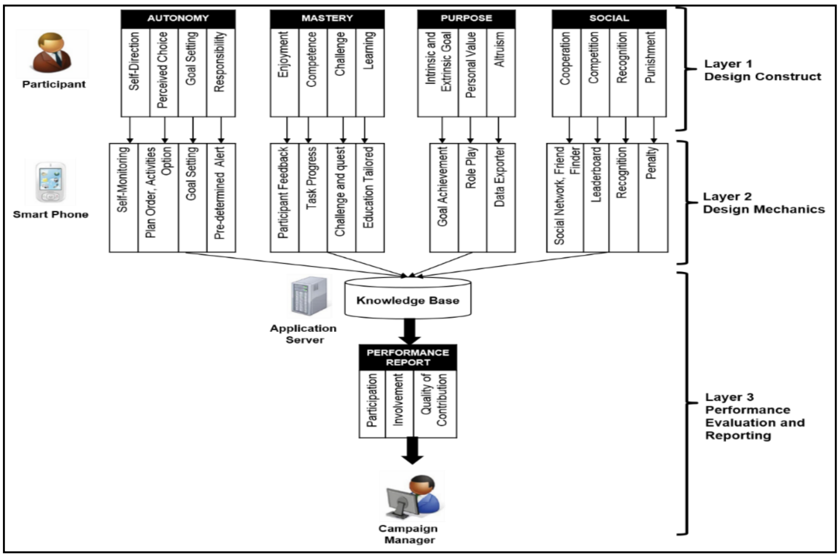

Figure 1: Proposed Design Guideline for Incentive Mechanics Using Hierarchical system Structure

Data Screening

In data screening, 283 weight loss apps were selected from the Google Play and App Store. Irrelevant apps that met exclusion criteria were excluded from the initial selection. Duplicate apps in Google Play and Apps Store that are similarly named from the same developer were removed from the dataset, leaving 247 apps for descriptive analysis. The descriptive characteristics of the apps were examined in Table 2.

Table 2: Descriptive characteristics of the examined apps

Analysis Categories		Frequency	Percent (%)
Market Type	Android	159	64.4
	Apple	88	35.6
Price Type	Free	217	87.9
	Paid	30	12.1
Developer Type	Company	30	12.1
	Individual or Developer Group	156	63.2
	Non-Profit Organization	61	24.7
Content Type	Function Oriented	68	27.5
	Information and Function Balanced	44	17.8
	Information Oriented	135	54.7

Figure 2 shows the breakdown apps screening from the dataset at various stages throughout the initial app inclusion assessment. One hundred and seventy-seven apps of 247 apps were eliminated after failing to meet the inclusion criteria related to price type, developer type, and content type.

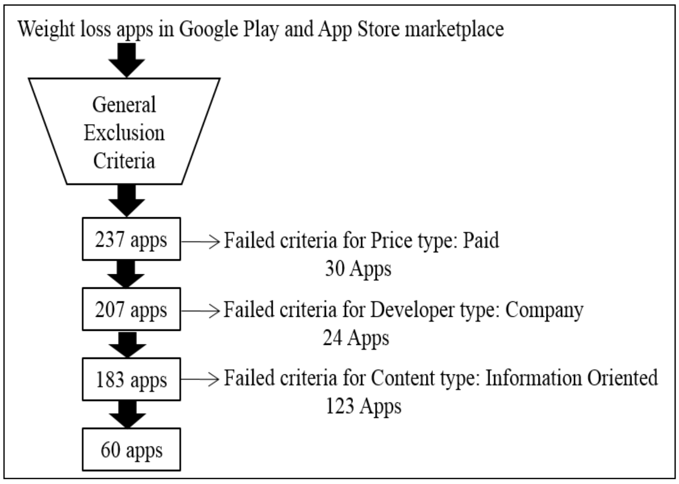

Figure 2: Flow Diagram of the App Inclusion Process

From the analysis, it can be seen that most of the apps are free for smartphone users. That being said, 54.7 percent of the apps in the market are information oriented, in which users are only allowed to view information related on dietary information, but not to actually experience the mobile health monitoring.

RESULTS

This study used two analysis: descriptive analysis and inter-coder analysis to establish reliability of the design guideline and to ensure the validity of the findings. The findings of the study are presented in the following sections.

Descriptive Analysis

In the descriptive analysis, the prevalence of incentive mechanic features is analyzed. The first set of analyses examined the distribution of the incentive mechanics across weight-loss applications. In Figure 3, number of apps that contain a minimum of one incentive mechanic features is accounted. In the figure, there is a clear trend of decreasing number of mechanics from intrinsic to extrinsic incentives, in which 95 percent of mobile health apps include at least one mastery mechanic features, followed by autonomy (88.3 percent), purpose (61.7 percent), and social (18.3 percent). From the chart, it can be seen that by far the greatest occurrence is for intrinsic incentives compared to extrinsic incentive mechanics.

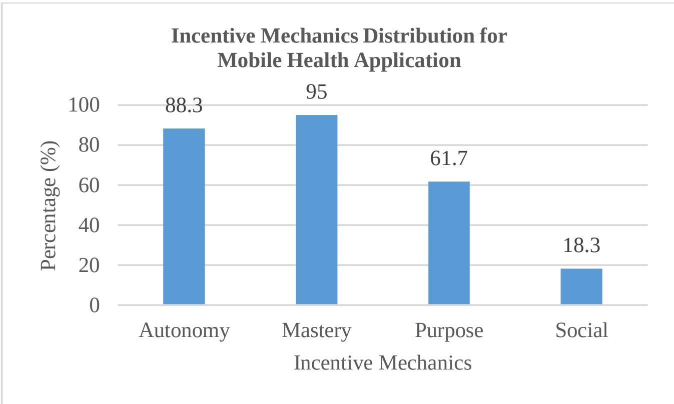

Figure 3: Incentive Mechanics Distribution for Mobile Health Application

The details of the incentive mechanics distribution are shown in Table 3. Under autonomy mechanics, 58.3 percent of the apps allow for continuous self-monitoring by recording information, while 43.3 percent of the apps provides user-defined target goal. The most notable features in the apps are the features that provide basic educational materials (56.7 percent), provide cues to achievement or progress (53 percent), and allow participant to express enjoyment and satisfaction of doing task (40 percent). It is apparent from Table 3 that features under purpose and social mechanics reported lower values than the other two groups, which is generally below 10 percent, except for goal achievement mechanics that display intrinsic or extrinsic achievement.

The coders were first given a start list of tools that represents the incentive mechanics features in the application. The list of tools is particularly important to identify which tools usually represent each of the incentive mechanic in the mobile health application.

Then, the list is built incrementally by the coders to ease up the coding process. Consistency of what to be included in the list of tools is particularly important because judgement of the features varied between the coders. Therefore, a consensus must reached between the coders for each new tools to be added in the list. Table 4 presents a list of tools used for the incentive mechanics.

Table 3: Incentive Mechanic Features Distribution

Analysis Categories		**Frequency**	**Percent (%)**
Autonomy	Allows continuous self-monitoring by recording information	35	58.3
	Information addressing purpose of user participation	15	25
	Allows individual plan to lose weight	6	10
	Offers at least more than one way to complete task	9	15
	Acknowledges individual perspective and user feedback	16	26.7
	Provides user-defined target goal	26	43.3
	Prompts the user to partake in a specific behavior through the use of a predetermined alert	17	28
Mastery	Allows user to express enjoyment and satisfaction of doing task	24	40
	Cue to achievement or progress	32	53
	Provides plan of action for reaching target goal	11	18.3
	Allows user to increase skills/ modify behavior	7	11.7
	Offers user-specific education tailored to a user's needs	14	23.3
	Provides basic educational materials	34	56.7
Purpose	Displays intrinsic or extrinsic achievement	13	21.7
	Duty or obligation to satisfactorily perform or complete an assigned task	5	8.3
	Allows user to send data/info to service provider	3	5
	Allows user to contribute to the community	7	12
Social	Allows user to communicate and find other participant	7	12
	Allows user to compete with each other	4	6.7
	Offers reward as an objective is achieved	4	6.7
	Offers reward as the more participant is engaged/involved in activities	4	6.7
	User will have a consequent penalty for failure	1	1.7

Table 4: List of Tools for Incentive Mechanics.

Construct	Incentive Mechanics	Tools
Autonomy	Self-monitoring	Daily calorie tracker
	Plan and orders	Different type of diet plan
	Activities option	Many ways of inputting calories, Notes, diary, q&a
	Goal setting	Goal setting input/update
	Pre-determined alert	Reminder
Mastery	Participant feedback	Rating system, like, emoticon
	Task progress	Progress bar, graph, feedback prompt
	Challenge and quest	Fitness activity option, BMI change
	Education tailored	Calorie budget, BMI calculator
Purpose	Goal achievement	Rating system, like, emoticon
	Personal duty	Role play, expert consultation
	Data exporter	Export of data (email, submission)
Social	Social Network	Social media, message/notification Community forum, message board, chat room
	Friend finder	Find friend through GPS or similar interest
	Leader board	Leader board (progress percentage/ranking)
	Recognition	Point, trophies, movement label, badges
	Penalty	Point deduction, participant elimination

Based on this analysis, the top weight-loss apps are identified. From the descriptive analysis, nine apps had at least one feature that tapped each of the autonomy, mastery, purpose, and social mechanics. The apps are sorted based on incentive mechanics occurrence. The first five of top-ranked apps are shown in Table 5.

Table 5: Top-ranked weight loss application.

Rank	Name of application	Market Type
1	Lose It! - Weight Loss Program and Calorie Count	Apple/Android
2	My Diet Coach	Apple/Android
3	Calorie Counter & Diet Tracker by MyFitnessPal	Apple
4	Inlivo	Apple
5	Jillian Michaels Slim-Down	Apple/Android

Inter-coder Reliability Analysis

The researcher used ReCal2 [20], an online tool to calculate the reliability. Even though the coders had been provided with training, the inter-coder reliability process was performed on the same case, in parallel, in an ongoing basis throughout the coding process to allow constant feedback on the quality of the coding. A good way to do this ongoing computation of agreement is to give coders a percentage of cases (80 percent) which are coded by all coders. In order to calculate an inter-coder reliability statistic all coders need to code the same case so that it is parallel. Features for initial construct assessment were revised between the researcher and coders if the agreement between the coders did not reach a percentage of 80 percent for cases.

The final incentive mechanics assessment for each feature is shown in Table 6. The inter-coder reliability assessment is presented using two measurements, Krippendorff's Alpha value and percent of agreement. Krippendoff method only accepts alpha that have results higher than 0.667. Based on the inter-coder reliability assessment, the features are sorted based on incentive mechanics reliability. The first five of most reliable features are shown in Table 7

Table 7: Top Five Most Reliable Features.

No.	Name of features	Mechanic	Construct
1	Allows continuous self-monitoring by recording information	Self-monitoring	Autonomy
2	Provides user-defined target goal	Goal-setting	Autonomy
3	Offers reward as an objective is achieved	Recognition	Social
4	Allows user to express enjoyment and satisfaction of doing task	Participant feedback	Mastery
5	Offers user-specific education tailored to a user’s needs	Education-tailored	Mastery

Table 6: Inter-coder Reliability (N =60)

Analysis Categories		**Krippendorff's Alpha**	**Agreement (%)**
Autonomy			
Self-monitoring	Allows continuous self-monitoring by recording information	0.796	90
	Information addressing purpose of user participation	0.504	81.7
Plan and orders	Allows individual plan to lose weight	0.082	83.3
Activities option	Offers at least more than one way to complete task	0.222	80
	Acknowledges individual perspective and user feedback	0.698	88.3
Goal setting	Provides user-defined target goal	0.798	90
	Duty or obligation to satisfactorily perform or complete a task that assigned.	0.135	86.7
Pre-determined alert	Prompts the user to partake in a specific behavior through the use of a predetermined alert	0.544	81.7
Mastery			
Participant feedback	Allows user to express enjoyment and satisfaction of doing task	0.757	88.3
Task progress	Cue to achievement or progress	0.668	83.3
Challenge and quest	Provides plan of action for reaching target goal	0.37	81.7
	Allows user to increase skills/ modify behavior	0.038	80
Education tailored	Offers user-specific education tailored to a user needs	0.723	90
	Provides basic educational materials	0.698	85
Purpose			
Goal achievement	Displays intrinsic or extrinsic achievement	0.698	90
Personal duty	Allows duty or obligation to satisfactorily perform or complete an assigned task	0.135	86.7
Data exporter	Allows user to send data/info to service provider	0.304	93.3
	Allows user to contribute to the community	0.358	86.7
Social			
Social Network and Friend finder	Allows user to communicate and find other participant	0.679	93.3
Leader board	Allows user to compete with each other	0.549	95
Recognition	Offers reward as an objective is achieved	0.734	96.7
	Offers reward as the more participant is engaged/involved in activities	-0.053	88.3
Penalty	User will have a consequent penalty for failure	-0.008	96.7

DISCUSSION

The purpose of this study is to construct a design guideline by mapping a set of behavioral incentive constructs obtained in the quantitative study into incentive mechanic features for mobile health participatory sensing system. The design guideline attempt to address the challenge on how the behavioral non-monetary incentives should be represented in a participatory sensing system. In order to validate the design guideline, descriptive analysis and inter-coder reliability analysis are performed on a representative sample of weight-lost apps (N=60) accessible in Malaysia.

The results obtained from the descriptive analysis show that a relatively small proportion of the apps (15 percent), addressed at least one feature that tapped each of the incentive mechanics. Almost all apps contain a minimum of one intrinsic incentive mechanic features. Despite most smartphones' social networking capabilities, the most revealing observation to emerge from the data comparison is that only 18.3 percent of the apps provide social features to the participant. The findings observed in this study mirror previous content analysis for mobile health monitoring apps. A number of authors have reported analysis of trends in inadequate number of social mechanic features in diabetes apps [21], smoking cessation apps [18] and cancer management apps [22]. A possible explanation for these findings may be due to ongoing concern for researchers and developers in privacy and security issues in mobile health, particularly when involving sensitive information and treatment [23].

Based on the results in Table 6, this study found 13 out of 23 (56 percent) of incentive mechanic features with low inter-coder reliability. Based on Krippendoff result, the lowest feature is "User will have a consequent penalty for failure" with -0.008 value from penalty mechanic, though the feature has the highest agreement, 96.7 percent. The low value of alpha may not necessarily reflect low level of agreement. The reason for the discrepancy between the level of agreement and alpha is the prevalence of penalty feature in all cases is very low [24]. The results corroborate the findings of the survey, in which items related to punishment is dropped during factor analysis. Many of the features with low reliability are from extrinsic incentives. However, one surprising finding reveals that both features under challenge and quest mechanic are of low reliability, where the researcher considers an important dimension for mastery.

In this study, the top-most reliable mechanic is self-monitoring under autonomy construct. In order for the mobile health apps to be effective particularly with the absence of supervision by medical practitioner, the apps must be able to allow for self-directive behavior. The ability of participants to log, set, manage, and monitor their progress toward their health goal was an important intrinsic incentive for using self-management tool. The effort involved for self-monitoring can be reduced by using photos to document complex input or connecting to wearable devices to automatically log participants' behavior. This can be seen in Lose it! app, where it allows automatic calories lookup on the online database based on meal pictures and using sensors to connect with blood pressure monitor.

CONTRIBUTION

This paper provided both theoretical and practical contributions. On the theoretical aspect, the theory-driven mapping of four incentive variables in the guideline: autonomy, mastery, purpose, and social; into incentive mechanics lends a useful guideline to analyze and assess weight-loss apps in the markets. The guideline enlightens the type of incentive mechanic features that is required in mobile health participatory sensing system to improve participants' performance and promote long-term behavioral change. This study is significant in that it provides empirical assessment on the incentive mechanics and their features that have been proposed in the design guideline.

On the practical aspect, the mapping of the incentive mechanic features is new in the participatory sensing literature. Therefore, the design guideline will shift research on non-monetary incentives towards being of more practical value to practitioners. The design guideline for non-monetary incentives mechanics and its features may aid system developers and service providers to implement the incentive concepts into practical systems' features and further improve participatory sensing system using the incentive mechanics addressed in this study. Moreover, the content analysis on the proposed incentive mechanics also provides system developers and service providers with empirical data that show which incentive mechanic features are deemed reliable.

CONCLUSION AND FUTURE WORK

In summary, this paper presented a design guideline that maps the identified non-monetary incentive constructs from Self-determination theory and Motivation 3.0 onto incentive mechanics in participatory sensing system. To provide validation of the proposed guideline, a content analysis was performed on 283 weight-loss apps from the market. After data screening, 60 apps were analyzed using descriptive and inter-coder reliability analysis. The primary findings of the survey analysis showed that many of the features with low reliability are from extrinsic incentives as prevalence of social mechanic features in all cases is low.

The design guideline of incentive mechanics is short of concrete realization. The design guideline does not simulate the dynamic operations between the incentive mechanics when specific behavior is learnt from the participants during the data collection activities. Further work is required to investigate and accommodate these issues. Future extension of the design guideline for incentive mechanic features will include and put an emphasis on simulating detail of an inter-relationship between each of incentive mechanics and module and their constituent factors. This involves developing a computational model for self-adaptive intrinsic incentives based on the proposed conceptual framework. Once the incentive mechanic features are learnt for specific participant behavior, machine learning technique may be used to confirm the elements in each framework component, and refine the relationships between the framework components.

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