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Towards Incentive Management Mechanisms in the Context of Crowdsensing Technologies based on TrackYourTinnitus Insights

Kushal Agrawal[a,*], Muntazir Mehdi[a], Manfred Reichert[a], Franz Hauck[a], Winfried Schlee[b], Thomas Probst[c], Rüdiger Pryss[a]

[a] *Ulm University, Institute of Databases and Information Systems, James-Franck-Ring, Ulm, 89081, Germany*
[b] *University of Regensburg, Department of Psychiatry and Psychotherapy, Universittsstrae 84, Regensburg, 93053, Germany*
[c] *Danube University Krems, Department for Psychotherapy and Biopsychosocial Health, Dr.-Karl-Dorrek-Strae 30, Krems 3500, Austria*

Abstract

The increased use of mobile devices has led to an improvement in the public health care through participatory interventions. For example, patients were empowered to contribute in treatment processes with the help of mobile crowdsourcing and crowdsensing technologies. However, when using the latter technologies, one prominent challenge constitutes a continuous user engagement. Incentive management techniques can help to tackle this challenge by motivating users through rewards and recognition in exchange of task completion. For this purpose, we aim at developing a conceptual framework that can be integrated with existing mHealth mobile crowdsourcing and crowdsensing platforms. The development of this framework is based on insights we obtained from the TrackYourTinnitus (TYT) mobile crowdsensing platform. TYT, in turn, pursues the goal to reveal insights to the moment-to-moment variability of patients suffering from tinnitus. The work at hands presents evaluated data of TYT and illustrates how the results drive the idea of a conceptual framework for an incentive management in this context. Our results indicate that a proper incentive management should play an important role in the context of any mHealth platform that incorporates the idea of the crowd.

Keywords: Crowdsourcing; Crowdsensing; Tinnitus; Incentives; Data Analysis; mHealth; eHealth; Incentive Management

1. Introduction

With the advent of digitization in the medical domain, many examples have shown that the collaboration between doctors and researchers from medicine and computer science is becoming more and more important. For example, the discovery of knowledge could be improved by applying technical approaches to medical questions [2]. Along the digitization trend, the goal to prevent factors that may negatively affect one's health is increasingly pursued. 4P Medicine (Predictive, Personalized, Preventive and Participatory), an initial idea in medicine and first coined by

* Corresponding author. Tel.: +49-731-5024129 ; Fax: +49-731-5024134
E-mail address: kushal.agrawal@uni-ulm.de

systems biologist Lee Hood [13], draws an interesting picture of how crowdsourcing and crowdsensing technologies can be a first point of contact for patients to give them initial thoughts on their medical condition and furthermore share a holistic view of the condition in the associated community. However, to get the best of these technologies, especially in the eHealth and mHealth domains, an interdisciplinary approach is crucially required. In this context, mobile crowdsensing techniques are particularly promising for new insights on chronic diseases.

In the TrackYourTinnitus (TYT) project, we aim at revealing new insights on tinnitus [11, 8, 10]. The latter is a chronic disorder that affects approximately 10% (42 million) of the total European Union population (425 million). Note that research on tinnitus is particularly challenging as it is a medical condition that is characterized by a large heterogeneity of symptoms and patient profiles. As a consequence, governments within the EU have spent billions of Euros in their respective health care systems [12].

In the context of TYT, a remarkable aspect that can be observed is the heterogeneity of the participation of its registered users [9]. This participation, in turn, indicates the overall motivation of the users to utilize the platform. Since TYT – and also other mHealth crowdsensing platforms – pursue the goal to gather large amounts of data that can be evaluated to work on new medical insights, including new treatment methods, the motivation of users to provide data is a fundamental pillar. As still many TYT users only provide less data or leave the platform early after using it for the first time, the question arises, how the overall user motivation can be increased. For this purpose, we developed a conceptual framework that deals with incentives to motivate patients in using the TYT platform more frequently. The framework as well as its core considerations are presented in this paper.

The remainder of this paper is structured as follows. In Section 2, we discuss background information that are relevant in the context of this paper. Section 3 then discusses revealed aspects of TYT that might be starting points for an incentive management for TYT in particular and similar platform in general, while Section 4 discusses possible further actions based on these insights. In Section 5, related work is discussed and Section 6 concludes the paper with a summary and an outlook.

2. Background Information

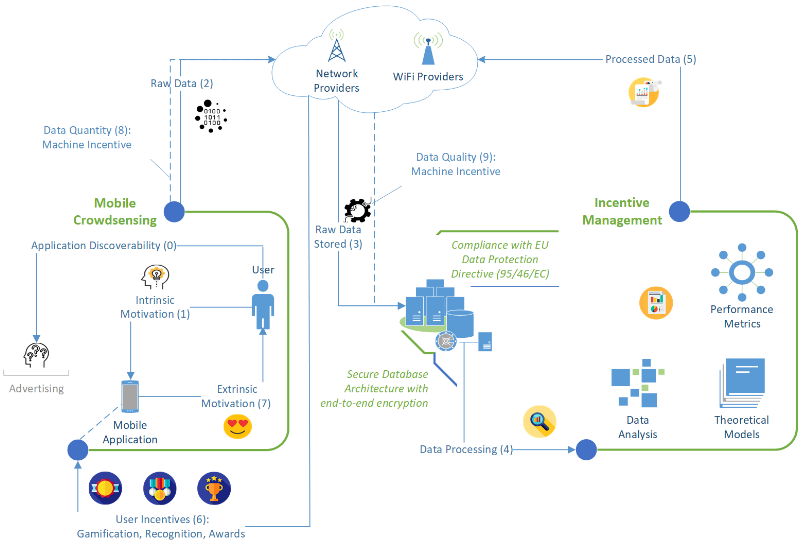
This section briefly discusses the required background aspects on mobile crowdsensing, incentive management, and TrackYourTinnitus,

2.1. Mobile Crowdsensing

The increased use of mobile devices and the Internet of Things have fostered the utilization of mobile crowdsensing (including mobile crowdsourcing) technologies to improve the public health care across the globe, especially in biomedical and clinical sciences [5]. At the very core, Mobile Crowdsourcing (MCR) advocates a proper user involvement to solve real-world tasks through the use of mobile devices and crowd users. Mobile Crowdsensing (MCS), in turn, encompasses the implicit and explicit collection of sensor data through the internal and external mobile device sensors in order to accomplish sensor tasks in different domains and contexts. Thereby, the applied sensors are able to record not only personal attributes like the GPS location, but also environmental information such as air pressure, temperature or noise level in relation to the surroundings of the respective device. In addition, while sensing data, questionnaires can be used to gather even more valuable data as users can subjectively evaluate the context or their individual situation.

2.2. Incentive Management

One fundamental challenge in the landscape of MCR and MCS constitutes the consideration of user motivation mechanisms [3]. Another frequently identified challenge in this context deals with low data quality [3]. Following this, Incentive Management (IM) is a mechanism that offers benefits or rewards to the system participants that requires the achievement of specific goals or the completion of certain activities. Today, IM is increasingly used in various industries and research fields. Thereby, IM techniques focus on the concrete actions and methods to increase the motivation of the participants, either by offering rewards or recognition [15]. To give some examples, commercial applications like Badoo, Duolingo, Facebook and so forth use IM techniques to keep their users motivated. Thereby, higher user motivation normally leads to more accurate data, which increases the overall data quality. Interestingly, in research projects, IM mechanisms are less utilized compared to industry projects [7]. For this purpose, we pursue the development of a conceptual framework for incentive management that deals with MCS in the context of e-health and m-health applications (cf. Fig. 1). The framework is based on existing insights and evaluations of the TrackYourTinnitus platform [11, 9]. In general, the methods that will be applied to realize the framework are: (a) theoretical models, (b) performance metrics, and (c) data evaluations. The use of theoretical models shall help to understand the strategic behavior of the participants, while performance metrics shall help to design and maintain a robust system. Finally, the data evaluations are focused on aspects that may reveal insights to increase the overall user motivation to use a platform like TYT.



Step	Process	Goal
0	Application Discoverability	Out of Scope (Advertising)
1	Intrinsic Motivation	Focused on these Users
2	Raw Data	Secure Collection of Data
3	Raw Data Stored	Secure Storage of Data
4	Data Processing	Data Analysis based on I.M*
5	Processed Data	Secure Transfer of Results
6	User Incentives	Keeping User Motivated
7	Extrinsic Motivation	Create User Engagement
8	Data Quantity	Continuous Data Collection
9	Data Quality	Continuous Data Improvement

* Incentive Management

Fig. 1. Conceptual Framework for Incentive Management

2.3. *TrackYourTinnitus*

This section gives relevant background information on TYT. The TYT mobile crowdsensing platform aims at measuring fluctuations of tinnitus perception and tinnitus distress under real-life conditions during the patient's day. In particular, mobile crowdsensing services shall enable researchers to gather data from huge numbers of users. Note that this allows tracking the moment-to-moment fluctuation of the tinnitus. Furthermore, tracked data may be related to everyday behavior as well as the daily routine of patients to systematically identify relationships between individual routines and tinnitus fluctuations. Technically, the platform comprises a website for user registration, two mobile applications (for iOS and Android), and a MySQL database as a central repository for the data collected, which can be made available to the clinicians and researchers upon request.

Currently, for all registered TYT users as well as TYT in general, no advertisements or marketing efforts were made. A first promising direction to deal with the motivation of TYT users is an in-depth analysis of the procedure users have to accomplish. Thereby, the question arises whether the procedure is bothering for TYT users or not. Consider therefore Fig. 2, it depicts a BPMN (Business Process Model and Notation) diagram [14] showing the journey a user has to accomplish when using TYT. Note that all manual user tasks are marked with a user icon and the automated script tasks (i.e., mainly connection issues with the TYT backend) are marked with the page icon. When using TYT for the first time, users have two general paths that can be chosen by them, either register/login through the website or download the application from the respective app store (iOS or Android). Following this, users must answer a first set of questionnaires (i.e., Registration Questionnaires), which contains 51 questions in total. The questionnaires help to understand the medical tinnitus history of users. However, users gets 3 options at this stage to continue their journey: (*a*) don't answer, (*b*) partly answer or (*c*) entirely answer all Registration Questionnaires (RQ). When a user opts for path *a* or *b*, the overall TYT user journey ends. To be more precise, only when users have either answered or skipped all 51 RQ, they can use the Assessment Questionnaire (AQ). The latter measures the subjective tinnitus of the users based on 8 questions [9] on a random and daily basis. Based on this initial TYT phase and the procedure as well as facts shown in Fig. 2, the following aspects can be observed:

- It might be the case that the overall journey to use TYT needs more explicit explanations. For example, a note that after registering through the website, the next step should be to download the mobile app may be helpful.
- It might be the case that the overall journey to use TYT has too much loose ends.
- Currently, less motivation mechanisms are applied. The general motivation of users is based on the intrinsic motivation to learn more about the individual tinnitus (cf. Fig. 2 ①). To complete the RQ, a patient gets no motivating factors (cf. Fig. 2 ②). On the other hand, it is compelling to complete them. This might bother the users. Finally, to fill out the daily AQ, the only applied motivating factor constitutes of receiving notifications (cf. Fig. 2 ③).

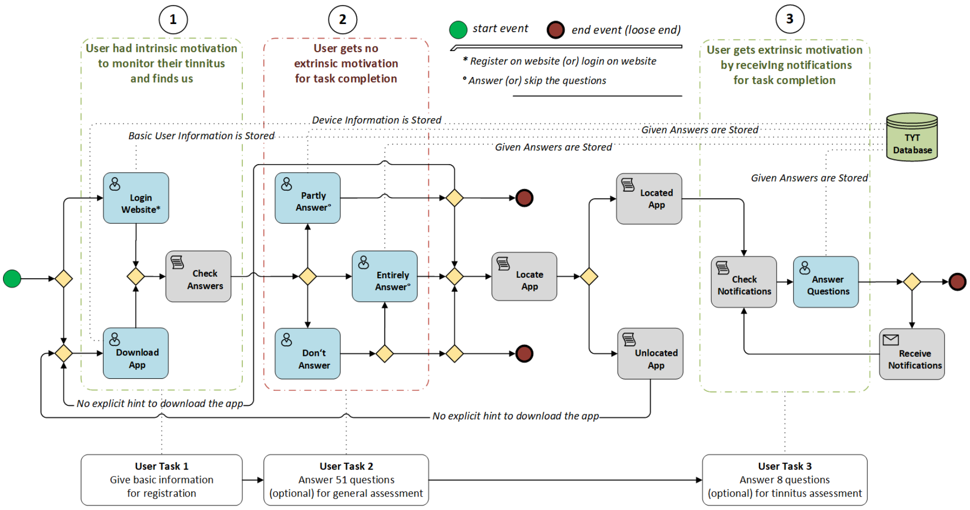


Fig. 2. TYT User Journey in Terms of a Business Process Model and Notation

2.4. *User Motivation in TrackYourTinnitus*

According to report from 2013 of the World Health Organization (W.H.O) [7], it was found that most of the eHealth applications on the market were made from a commercial perspective rather than a research one. Moreover, it was discovered that the industry had focused only on four of the eight most prevalent medical conditions. The report also revealed that the applications designed for assisting or monitoring the medical condition were used more frequently than the ones that were designed for simple informative purposes. Finally, it was also observed that the data visualization was mainly in a textual style and, hence, in most cases the user-interface was perceived as being counterintuitive [7]. Therefore, it is important to consider the target audience when designing the applications. For example, if most of the application users are elderly people, then it is less likely that they have a high-end smartphone and/or use features that demand a sophisticated user interaction. When looking at TYT from the user journey perspective, we may observe that we need to address the current challenges similar to the ones found in W.H.O report [7]. Primarily, we need to motivate TYT users at each stage of their application journey. This would help us to retain users that we lose at the first set of questionnaires i.e. RQ, as can be identified from the differences in the unique user numbers shown in Table 2. The latter shows that the number of users that fill out the RQ is much higher than the number of users that fill out the AQ. Following this, the number of users we lose for the AQ probably leave the platform during/after accomplishing the RQ and do not return. Moreover, we also might need to make the user interface more intuitive and easy to use for both Android and iOS users.

3. Data Analysis on TrackYourTinnitus

This section discusses aspects we revealed from TYT that might be valuable starting points for an incentive management for TYT in particular and other platforms coping with the management of chronic diseases in general. Some basic statistics from the TYT database are illustrated in Table 1. Currently (April 2018), we have a total of 2039 unique users that either registered on the website or through the mobile apps. From these 2039 users, we have 25.60% users (522) that answered at least one of the 51 questions in the RQ set. Since these questions had no validation checks, it was possible that the users simply skipped the questions and moved onto the next one. We got 75.33% (1536) of the total users that used the AQ at least once to evaluate their subjective tinnitus [9]. Following this, we lost a total of 24.67% users from the first RQ set to the AQ. Furthermore, we may also observe that the users gave preference to convenience over privacy by allowing the TYT app to remember their credentials. More specifically, 83.77% users opted to remember their email address and 65.96% opted to remember their credentials for the next login.

Table 1. Descriptive User Statistics based on Registration and Assessment Questionnaires

	Registration Questionnaire	**Assessment Questionnaire**
Unique Users	2039	1536
Unique Countries	95	84
Remember Credentials	1345	973
Save Email	1708	1282

Another interest aspect concerning user motivation constitutes the distribution of given answers to the eight questions of the AQ (cf. Fig. 3). Thereby, the x-axis represents the scale from 0 to 1 and y-axis represents the number of times users have answered the question. Interestingly, for Questions 2, 3, and 6, a similar pattern can be observed, which might be a valuable direction. For example, it might be the case that we can relieve users from answering Question 3 and 6 if they have answered Question 2.

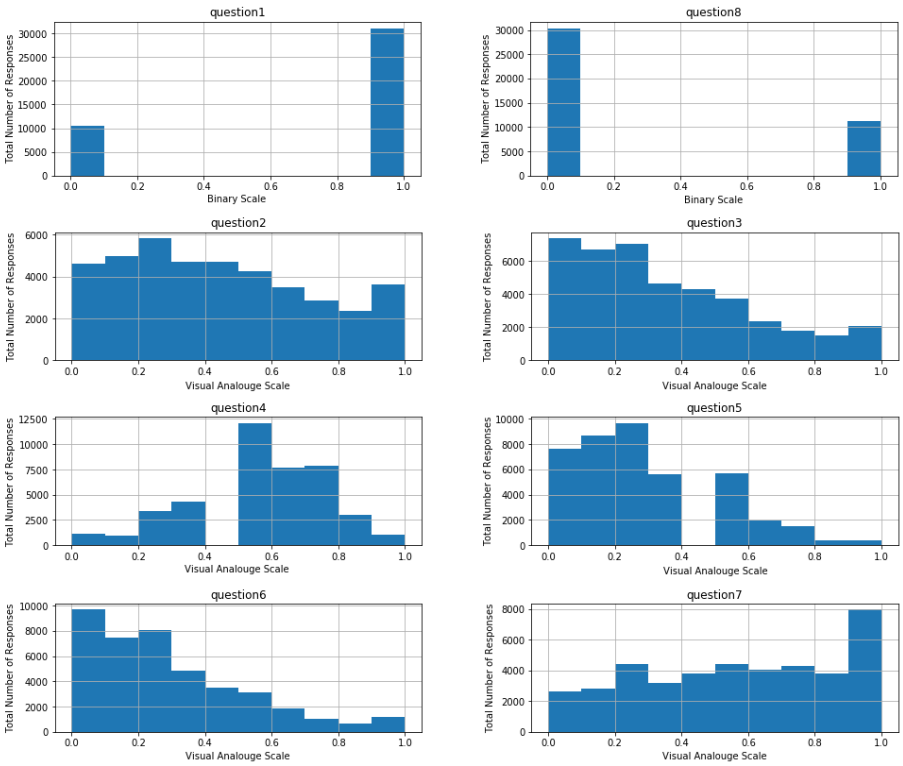


Fig. 3. Distribution of User Data for Assessment Questionnaire

The next interesting aspect emerges when having a look at the used mobile operating systems and mobile devices (cf. Table 2). Note that the total number of device users are greater than the total number of unique users. This is due to the fact that a user might have used multiple devices or updated the device software. In both cases, this scenario is regarded as a new device. Furthermore, the lost users column indicates the number of users that answered or went through all the RQ, but never started answering the AQ. To be more precise, 41.11% of all users, of which 3.86% were iOS and 30.14% Android users, got lost after or during the RQ. Moreover, the numbers also show that from the total iOS users, 9.23% were lost, whereas from the total Android users, (alarming) 60.56% were lost.

Table 2. User Statistics based on Mobile Devices

Mobile Platforms	**RQ Answers (N)**	**AQ Answers (N)**	**Lost Users (N)**	**Lost Users (%)**
iOS 11	109	87	22	20.18%
iOS 10	406	262	144	35.48%
iOS 9	345	340	5	1.45%
iOS 8	231	295	0	0.00%
iOS 7	143	140	3	2.10%
iOS 6	12	7	5	41.64%
Total iOS Users	**1246**	**1131**	**115**	**9.23%**
Samsung Android	715	310	405	56.64%
HTC Android	140	27	113	80.71%
Sony Android	139	41	98	70.50%
LG Android	134	58	76	56.72%
Motorola Android	76	25	51	67.11%
Huawei Android	57	25	32	56.14%
Google Android	31	11	20	64.52%
Acer Android	9	4	5	55.56%
Other Androids	91	48	43	47.25%
Total Android Users	**1392**	**549**	**843**	**60.56%**
Unknown Platforms	159	0	159	100.00%
Total Device Users	**2797**	**1680**	**1117**	**39.94%**

The next aspect concerns notifications. The latter are being the only incentive for the users at the moment to fill out the AQ. Therefore, we analyzed both types of notifications that users can choose; i.e., standard notifications or custom notifications (cf. Table 3). Thereby, standard notifications are using a random approach, while custom notifications are applied to fixed points in time. An in-depth description of these notifications can be found in [10]. Primarily, we observe that even though unique devices for iOS is more than twice compared to Android, the ratio of standard and custom notifications for Android users is much higher than that of iOS. This means that from the total of iOS users that selected any type of notification, a iOS user receives nearly 12 standard and 32 custom notifications, whereas an Android user from the total Android users receives 43 standard and 49 custom notifications. Although we have a total of 1536 unique users, the total number of unique users in Table 3 shows that 1406 users own a total of 1532 devices. Following this, the 130 users that are getting lost here are the ones who never opted to receive any kind of notification.

Finally, we briefly show the pearson's correlations of the eight questions of the AQ (cf. Table 4). It is important to note that even though 2 different scales are used (i.e., binary scale for Q1 and Q8 and visual analogue scale for Q2 to Q7 [9]), the data is normalized as the minimum and maximum values of both the scales are constant at 0 and 1 respectively. Among the positive correlations, it can be observed that Q2 (Tinnitus Loudness) and Q3 (Tinnitus Distress) have a high correlation of 0.76, whereas Q2 (Tinnitus Loudness) and Q6 (Stress) have a partial correlation of 0.46. Moreover, we also observe an inverse relationship between Q4 (Mood) and Q6 (Stress), i.e, a negative correlation of 0.43. Some other interesting correlations are also revealed that may be analyzed in future work. Again, observed correlations may serve as a starting point to potentially relieve particular users from answering specific questions.

4. Discussion

The analyzed results lead to valuable insights. First, from Table 1 it can be observed that we lose a total of 24.64% users between the tasks to fill out the RQ and the AQ. It can be assumed that this is caused by the fact that no extrinsic motivation is provided between these two tasks. As the procedure to answer 51 questions (i.e., answers to the RQ) at stage one requires a lot of time, and the benefits of the apps are not obvious at this stage, motivating factors have to be established in this context. Second, as can be observed from Table 2, we lose more Android users compared to iOS users. This might be caused by a more appealing user interface of iOS. This explains the need of designing

Table 3. Statistical Analysis based on User Notifications

	Standard Notification (Unique)	**Custom Notification (Unique)**	**Standard Notification (Count)**	**Custom Notification (Count)**	**Standard Notification (Ratio)**	**Custom Notification (Ratio)**
iOS 11	69	20	318	268	4.61	13.40
iOS 10	208	73	1405	3459	6.75	47.38
iOS 9	327	21	5184	515	15.85	24.52
iOS 8	284	14	3415	38	12.02	2.71
iOS 7	134	9	1743	76	13.01	8.44
iOS 6	5	2	164	3	32.80	1.50
Total iOS	**1027**	**139**	**12229**	**4359**	**11.91**	**31.56**
Samsung Android	289	31	11992	1629	41.49	52.55
Sony Android	38	5	2928	10	77.05	2.00
HTC Android	26	2	2545	847	97.88	423.50
LG Android	53	10	1448	364	27.32	36.40
Motorola Android	24	2	1280	30	53.33	15.00
Huawei Android	20	5	336	156	16.80	31.20
Google Android	9	2	190	225	21.11	112.50
Acer Android	4	0	137	0	34.25	N/A
Other Androids	42	10	722	48	17.19	4.80
Total Androids	**505**	**67**	**21578**	**3309**	**42.73**	**49.39**
Total Devices	**1532**	**206**	**33807**	**7668**	**22.07**	**37.22**
Unique Users	1406	190	33807	7668	24.04	40.36
Unique Countries	79	43	79	43	1.00	1.00

Table 4. Pearson's Correlation Matrix based on Assessment Questionnaire

	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q6**	**Q7**	**Q8**
Q1	1.000000	0.291007	0.293499	-0.116032	-0.097226	0.145839	-0.056320	0.151996
Q2	0.291007	1.000000	**0.765348**	-0.314452	0.156495	**0.460751**	0.029596	0.151321
Q3	0.293499	**0.765348**	1.000000	-0.387188	0.163291	**0.627064**	-0.038636	0.241273
Q4	-0.116032	-0.314452	-0.387188	1.000000	-0.182392	**-0.435319**	0.034852	-0.238706
Q5	-0.097226	0.156495	0.163291	-0.182392	1.000000	0.370339	0.126928	0.132367
Q6	0.145839	**0.460751**	**0.627064**	**-0.435319**	0.370339	1.000000	0.045064	0.232880
Q7	-0.056320	0.029596	-0.038636	0.034852	0.126928	0.045064	1.000000	0.092731
Q8	0.151996	0.151321	0.241273	-0.238706	0.132367	0.232880	0.092731	1.000000

mechanisms considering the low end smart-phone compatibility. Third, when it comes to notifications as shown in Table 3, for most of the user cases in which the ratio of custom notification is higher than the standard notification, we can assume that they are more tech-savvy. This can be explained by the fact that setting the custom notifications requires extra effort, whereas for standard notifications this is done automatically. Third, based on the figures of Table 4, with the help of clinicians and psychologists, we can design new features (feature engineering) that will the help us to make more accurate predictions, which, in turn, can help patients to better understand their tinnitus.

5. Related Work

Incentive management in the context of crowdsensing is a relatively unexplored area, although we observe some promising work in the field in the last couple of years. A recent work from 2017 [4] illustrates the taxonomy of incentive mechanism specifically designed for health-related data. Thereby, [4] classifies the data collection into two broad categories of general purpose and specific purpose. However, the authors of [4] accurately identified the challenges with this taxonomy, i.e., quality of information, coverage, sample maximization, sample accuracy, and cost minimization that needs further attention. Another promising work was presented in 2012 [15], in which the authors designed incentive mechanism models using platform-centric and user-centric models. For the former model they used the *Stackelberg Game* and for the later they designed an auction-based incentive mechanism. Although they claim to have achieved a Stackelberg equilibrium, they do not show the backward induction to prove this equilibrium. Moreover, to the best of our knowledge, they designed two different models placing focus on platform utility maximization rather than to achieve an ecosystem equilibrium. Finally, *Amazons Mechanical Turk (MTurk)* [1] is a web-based solution and one of the biggest examples of crowdsourcing technology today. MTurk allows its users to register either as a requester, where one can create tasks and receive compensations, or as a worker, where one can earn money for task completion. However, MTurk has limitations in terms of ecological validity of conducted studies and robust support for participant assignments [6]. Moreover, MTurk is focused towards the micro-task markets and relies solely on monetary incentives.

6. Summary and Outlook

This paper gave insights into the TYT mobile crowdsensing platform with the goal to reveal aspects that can be the basis for an incentive management for TYT in particular and mobile crowdsensing platforms in the context of disease management in general. A conceptual framework was sketched, which is our basis for further developments in this context. The considerations the framework is based on were discussed along insights of the TYT platform. We showed that many analyzed results indicate that a proper incentive management can be addressed. One direction we currently pursue is the application of machine learning algorithms to reveal even more valuable insights to data that was gathered with TYT. In general, incentive management becomes increasingly important in the context of eHealth and mHealth applications and platforms.

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