Mobile Crowdsensing Services for Tinnitus Assessment and Patient Feedback

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***Abstract*—Assessment of chronic disorders requires new ways of data collection compared to the traditional pen & paper based approaches. For example, tinnitus, the phantom sensation of sound, is a highly prevalent disorder that is difficult to treat; i.e., available treatments are only effective for patient subgroups. In most individuals with tinnitus, loudness and annoyance of tinnitus varies over time. Currently, established assessment methods of tinnitus neither systematically assess this moment-to-moment variability nor environmental factors having an effect on tinnitus loudness and distress. However, information of individual fluctuations and the effect of environmental factors on the tinnitus might represent important information for tinnitus subtyping and for individualized treatment. In this context, a promising approach for collecting ecological valid longitudinal datasets at rather low costs is mobile crowdsensing. In the *TrackYourTinnitus* project, we developed an advanced mobile crowdsensing platform to reveal more detailed information about the course of tinnitus over time. In this paper, the patient mobile feedback service as a particular component of the platform is presented. It was developed to provide patients with aggregated information about the variation of their tinnitus over time. This mobile feedback service shall help a patient to demystify the tinnitus and to get better control of it, which should facilitate coping with this chronic health condition. As the basic principles and design of this mobile services are also applicable to other chronic disorders, promising perspectives for disorder management and clinical research arise.**

***Keywords*-Mobile Crowdsensing, Mobile Healthcare Application, Patient Feedback, Mobile Healthcare Service, Mobile Service.**

I. Introduction

Healthcare craves for new ways of collecting large and ecological valid longitudinal data. This applies to the assessment of tinnitus as well. Tinnitus is a highly prevalent disorder, for which currently no sufficient therapy exist [1]. Furthermore, Tinnitus is a purely subjective sensation that can only be assessed by the report of the individual patient. The pathophysiology of tinnitus is incompletely understood and clinical trials frequently reveal contradictory results. Presumably, these non-conclusive results can be explained by the fact that tinnitus is not a homogeneous clinical entity. Instead, there exist many forms of tinnitus, varying in their clinical characteristics as well as in the response to specific therapeutic interventions [2], [3]. Additional complexity is introduced by the fact that the perception of tinnitus loudness and distress is not constant in most cases, but varies over time depending on the context (e.g., environmental sound level or stress) [4].

Currently, tinnitus is assessed based on questionnaires, visual analogue scales or psychoacoustic measurements. However, these assessment methods, which are used both in clinical practice and research, do not capture the within-day and between-day variability of tinnitus loudness and distress over time. Moreover, contextual and environmental influence on Tinnitus loudness questions the current routine, where assessments are performed in most cases in clinics or at home, but practically never during work or any other activity of daily life. In order to mitigate these shortcomings, new ways of collecting ecological valid longitudinal datasets at rather low costs from patients during their daily life are required. For this purpose, we developed the mobile crowdsensing platform *TrackYourTinnitus* (TYT). The latter tracks individual tinnitus perception using smart mobile devices of users. The tracking procedure comprises a specific questionnaire we developed to assess tinnitus perception and tinnitus-related parameters during the daily routine of a user. Additionally, the smart mobile device of a user records the environmental sound level, while the user fills in the assessment questionnaire. Results are transferred to the *TYT* backend that, in turn, offers features enabling researchers to evaluate gathered patient data. Note that in the context of personalized healthcare, mobile crowdsensing offers completely new perspectives [4]–[7] on the daily routine of patients.

The analysis of the first data assessed with *TYT* [4], [8], [9] has confirmed the hypotheses of (1) a relevant variability of tinnitus loudness and annoyance for the majority of patients and (2) an interaction with exogenous and endogenous factors. These findings have high relevance for individual patients: The *TYT* may detect specific relationships between influencing factors and tinnitus annoyance, which have not been identified by patients in conventional studies before. For example, tinnitus annoyance may depend on the stress level the patient had the day before. Information of the patients about such relationships may (1) help gaining more control about a symptom that seemed to be completely uncontrollable, (2) provide guidance for behavior and thus help to better cope with tinnitus and perceive the tinnitus as less stressful. Moreover, smart feedback on tinnitus variability and influencing factors is expected to motivate users to use the mobile *TYT* services.

Such results highlight the potential of Ecological Momentary Assessment (EMA; also known as: ambulatory assessment & experience sampling), which is provided by TYT, to support clinicians in assessing neuropsychiatric symptoms accurately and in making valid diagnoses. In EMA, the variable in question (e.g., symptoms) is assessed repeatedly in daily life [10]. Instead of retrospectively asking the individuals (in an interview or questionnaire) how strong they experienced a symptom in a given past time interval, the individuals are asked how they currently experience the symptom; this is done at several time points within the given time interval.

This paper presents the mobile feedback service of the *TYT* platform. We provide detailed backgrounds, present technical issues, and discuss the perspective of patients on the feedback service. In this context, the developed feedback service is expected to increase general user motivation. The remainder of this paper is organized as follows: Section II introduces the *TYT* platform and its main features. In Section III, the mobile service for patient feedback is presented. Finally, Section IV discusses related work and Section V concludes the paper with a summary and outlook.

II. THE TRACKYOURTINNITUS PLATFORM

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. Moreover, the *TYT* mobile crowdsensing platform can be further developed to assess the effects of specific standardized therapeutic interventions.

We developed the *TYT mobile crowdsensing platform* as a multidisciplinary research team consisting of psychologists, physicians, and computer scientists. 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 [6], [11], which can be made available to the clinicians and researchers. The website also provides two important other features: (1) users can visualize their recorded tinnitus data and (2) users can provide information about their current tinnitus treatment. In order to be able to track the daily tinnitus perception, the following procedure must be accomplished by a user.

First, users have to create an TYT account using our website.

Second, after registering, users have to fill in three registration questionnaires. First, users have to fill in the "Mini-TQ-12" questionnaire, which measures tinnitus-related psychological problems. Second, users have to fill in the "Tinnitus Sample Case History Questionnaire (TSCHQ)". The TSCHQ questionnaire determines the current tinnitus status of the user as well as his tinnitus history. Finally, users have to fill in the "Worst Symptom" questionnaire. This questionnaire asks the user about his current worst symptom caused by tinnitus. While the first two questionnaires constitute already used instruments, the third one have been newly developed by the authors. Altogether, users have to complete 58 questions with respect to the three questionnaires. The completion of these three questionnaires is a prerequisite to be able to use the TYT website features as well as the mobile applications.

Third, after the registration questionnaires have been completed, a user can use the mobile applications to track the daily tinnitus perception. Therefore, the user has to log in to the Android or iOS mobile application. Then, he is asked to fill in the assessment questionnaire developed by us. The questionnaire comprises 8 questions (cf. Table I) and rates the tinnitus perception of the user when being asked (e.g., current tinnitus loudness).

Fourth, the assessment questionnaire, in turn, is provided in two ways: (1) the mobile application automatically applies the questionnaire to the user or (2) the user makes the conscious decision to fill in the questionnaire. The first way is our desired procedure and realized as follows: The assessment questionnaire is randomly presented to the user up to 12 times per day. Therefore, we realized a notification feature for Android and iOS as well as a notification algorithm [6]. This procedure of applying the assessment questionnaire ensures that (1) users cannot foresee the time of being asked and that (2) users are asked in various daily situations. Such a randomized approach was realized in order to improve the ecological validity of the method applied.

Fifth, while filling in the assessment questionnaire, the smart mobile device of a user records the environmental sound level. Currently, the sound level measurements are evaluated in more detail. One question, among others, that arises is based on the fact whether measurements of the iOS platform and the Android platform are comparable.

Sixth, finally, results gathered with the assessment questionnaire and sound recording are transferred to the TYT database. The latter, in turn, offers features enabling researchers to evaluate gathered patient data. This feature has been used for the results presented in this paper.

III. PATIENT FEEDBACK

Experiments we had conducted with the *TYT* platform and its mobile services revealed that proper feedback on the collected data is essential for users in order to increase their motivation for regularly using the mobile app. Note that

	Question	Scale	Measurement of
①	Did you perceive the tinnitus right now?	BS	Perception
②	How loud is the tinnitus right now?	VAS	Loudness
③	How stressful is the tinnitus right now?	VAS	Strain
④	How is your mood right now?	VAS	Mood
⑤	How is your arousal right now?	VAS	Arousal
⑥	Do you feel stressed right now?	VAS	Stress
⑦	How much did you concentrate on the things you are doing right now?	VAS	Concentration
⑧	Do you feel irritable right now?	BS	Irritability
	BS=Binary Scale, VAS=Visual Analogue Scale		

Table I: TrackYourTinnitus Assessment Questions

proper feedback constitutes a salient incentive for patient engagement in the context of mobile healthcare services in general [12]. Regarding tinnitus, for example, a well-designed feedback function should provide the patients with information that allows them to better understand the dependencies between tinnitus loudness and annoyance on environmental factors. This information shall help them to demystify tinnitus, to obtain an improved control, and to better cope with their tinnitus. Our results confirm that about 40 percent of the tinnitus variance can be explained with the variance of exogenous and endogenous factors. If individual users have understood this relationship, they can get better control over their tinnitus. Motivated by this data gathered with *TYT*, we developed a sophisticated mobile feedback service. The latter was integrated with both the *TYT* backend and the Android mobile application.

In general, different approaches for providing mobile feedback can be distinguished. First of all, feedback could be provided by medical experts based on the information gathered with the smart mobile device. Alternatively, feedback can be automatically generated by smart services and information systems respectively. Furthermore, the way how feedback is provided to users is essential. *TYT* comprises a mobile feedback service that automatically generates user feedback and additionally provides the option for transferring selected information to the treating physician, who can then give feedback. Whether feedback is based on real time data only or also considers historical data constitutes another differentiation. The *TYT* service considers historical data gathered with the assessment questionnaire. Based on this data, individual feedback is calculated automatically.

Finally, we learned that the ability to configure parameters relevant for feedback calculation is highly welcome by users. *TYT* allows them to specify a time window that shall be applied to the personal data gathered with the assessment questionnaire. If a user specifies the respective parameter, feedback calculation will be limited to the specified time window. Therefore, the parameter allows patients to check whether the received feedback has evolved over time.

This section presents the *TYT* mobile feedback service along three perspectives. First, we sketch the overall feedback procedure and present factors relevant in this context. Second, we discuss the user perspective on the feedback service. Finally, we present technical issues related to the developed feedback algorithms.

A. Overall Feedback Procedure

Fig. 1 gives an overview on the mobile feedback service. Its general idea is to categorize patients based on the collected data and to provide specific feedback depending on the category the patient is assigned to. Accordingly, patients are categorized based on their questionnaire data. The categorization of individuals will be calculated automatically. For example, if in a given individual the tinnitus loudness correlates with stress levels, the person will be automatically assigned to category *stress*.

Altogether, we identified four categories (cf. Fig. 1⑤). The four patient categories are derived based on analyses of the data collected by all *TYT* users (cf. Fig. 1②). Thereby, we focused on the correlation of subjective loudness (cf. Table I, *Question 2*) with other measurements (cf. Table I, *Questions 3-8*). If we had observed a particular correlation for a considerable subset of the patients, we derived a corresponding feedback category. This analysis revealed that a correlation with Question 1 is not relevant. Note that Question 1 solely considers the current tinnitus situation. That means, patients may not perceive the tinnitus right now, but perceive it in general. The remaining correlations for *strain* (cf. Table I, *Question 3*) and *irritability* (cf. Table I, *Question 8*) require further considerations before taking them into account.

Assigning patients to one of the four categories constitutes the first part of the feedback procedure (cf. Fig. 1⑤). Furthermore, each category is coupled with specific interpretations. These interpretations, in turn, are created by medical experts using the *TYT* backend and include, for example, general recommendations (cf. Fig. 1⑧). If a relationship between perceived stress and perceived tinnitus is detected, for example, the feedback about it further includes the information that there exist specific approaches for stress reduction (cf. Fig. 1⑥). These interpretations, in turn, are assigned to one or more of the categories, again with the help of the TYT backend (cf. Fig. 1⑥). Furthermore, interpretations are associated with detailed explanations that will be created by the medical experts as well. Patients may rate these explanations (cf. Fig. 1⑦) to inform the medical experts whether they have benefited from it. The interpretations together with the explanations constitute the second part of the feedback. Moreover, the two discussed parts form the entire feedback for an individual patient (cf. Fig. 1④). Technically, the feedback will be provided by the *TYT* mobile feedback service.

There are two additional aspects of the *TYT* mobile feedback service. **First**, we developed a metrics called *degree of reliability* (dor) (cf. Fig. 1⑨). The latter is calculated for

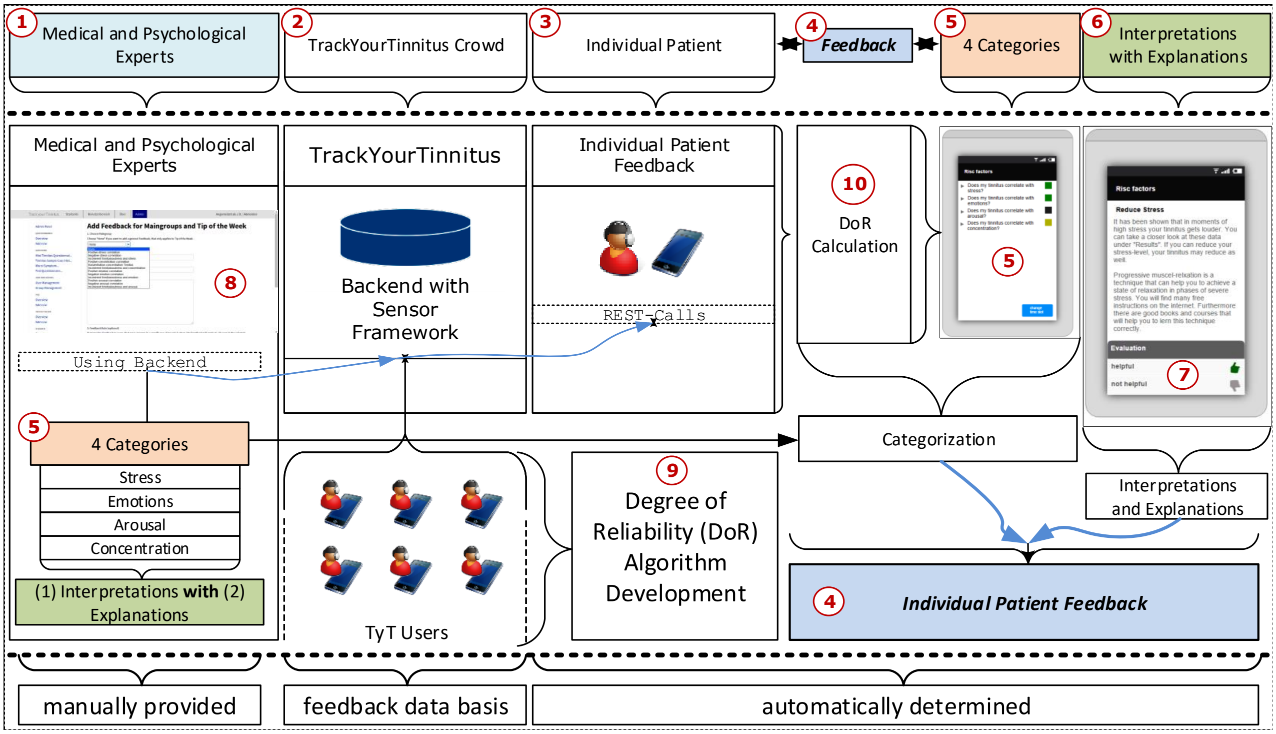

Figure 1: Patient Feedback Overview

each feedback category, indicating whether the amount of collected patient data is sufficient. To evaluate sufficiency for an individual patient, we considered collected data of all *TYT* users. Thereby, different perspectives were considered. For example, we calculated *dor* for category *stress* and related it to the amount of user notifications (cf. Fig. 2). Based on this, we developed a scale for *dor* as depicted in Fig. 4③. Note that *dor* ≥ 0.6 must hold in order to start calculating the correlation for a category. For example, if the calculated *dor* for category *stress* is less than 0.6, the calculation needed for deciding whether the patient belongs to this category will not be started. If there are not enough data for categorizing a user, the *TYT* mobile feedback service returns this information to *TYT* users. Note that each category is considered independently with respect to the needed amount of data. This allows patients to obtain direct and valuable feedback on their collected data. Either they unveil that not enough data was collected or that feedback evolves over time.

Second, the correlation of a category is based on the Pearson product-moment correlation coefficient (*PCC*) [13] (cf. Fig. 1⑩). Recall that the degree of reliability (*dor*) is coupled with the correlation calculation such that *PCC* is only calculated if *dor* ≥ 0.6 holds. To tie correlation calculation with the degree of reliability revealed two advantages: First, patients may compare their assignments among the four categories. For example, if a patient belongs to category *stress*, but not to *concentration*, more data needs to be collected with respect to *concentration* (cf. Table I Question 7). Second, the *dor* scale is based on all patients. Therefore, individuals will benefit from collected data of all *TYT* users.

B. Patient Perspective

Another fundamental perspective on the *TYT* mobile feedback service is the one of the patient. Fig. 3 presents examples of feedback screens regarding the smart mobile device of a patient. Additionally, the interactions between the screens are shown in Fig. 3. Patients use the feedback as follows: *First*, they click on *My Feedback* (cf. Fig. 3①). *Second*, after clicking on *My Tinnitus*, they configure the period of time for feedback calculation (cf. Fig. 3②). Note that Fig. 3② solely illustrates the specification of the start date for this calculation. Another screen is used for the end date. *Third*, the screen showing the categorization is presented to the mobile user (cf. Fig. 3③). Note that this screen is only presented if at least one degree of reliability of $\{$*mood, arousal, stress, concentration*$\}$ ≥ 0.6 holds (cf. Figs. 3③, 4②). In Fig. 3, for example, the result for category *arousal* indicates no correlation for the tinnitus of the respective patient, as the calculated degree of reliability is less than 0.6. *Fourth*, a patient may expand a category in order to get all interpretations assigned to this category (cf. Fig. 3④). If patients click on interpretations, the screen presented in Fig. 3⑤ is displayed. Finally, patients may return feedback to the selected interpretation (cf. Fig. 3⑧).

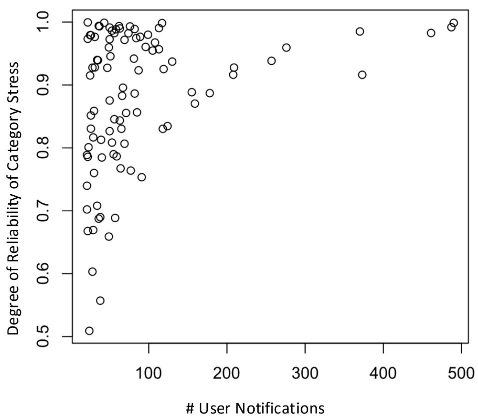

Figure 2: Degree of Reliability of Category Stress and User Notifications

	Name	Type	Explanation
PK	id	int	—
FK	user_id	int	—
	For detailed question explanations see Table I		
	question1	tinyint	—
	Next line represents 6 database rows		
	question2-7	float	Rows for Question 2 - Question 7
	question8	tinyint	—
	soundlevel	float	—
	save_date	datetime	Local Storage Time on Mobile Device
	notification_date	datetime	Local Notification Time on Mobile Device
	autosaved	tinyint	User Forgets Pressing Save Button $\rightarrow$ Try Automatic Save
	notification_fixed	tinyint	Indicates Notification Schema $\rightarrow$ Random (0) or Fixed (1)
	created_at	datetime	Storage Time on Remote Database
	user_agent	text	Device Attributes

SQL-Command for Date Input (startdate,enddate) of User $feedbackuser

SQLF=*"SELECT question2, question4, question5, question6, question7 FROM 'standardanswers' WHERE user_id = $feedbackuser and (created_at BETWEEN $startdate AND $enddate) ORDER BY question2 ASC"*

— = no explanation needed due to name of row

Table II: Entity $standardanswers$

C. Technical Perspective

We developed two algorithms for calculating proper user feedback. One of them determines the degree of reliability (*dor*), the other algorithm assigns patients to one of the four categories presented; e.g., if the tinnitus loudness correlates with stress of the respective user, the user will be assigned to the category *stress*. Note that both algorithms operate on the patient data gathered with the mobile assessment questionnaire. This data, in turn, is captured by entity $standardanswers$ (cf. Table II).

As shown in Table II, entity $standardanswers$ comprises 17 attributes. In the context of the two algorithms, several of these attributes are considered: First, attributes $question2$ and $question4$-$question7$ are used to calculate the degree of reliability as well as the assignment of users to categories. Second, attribute $user\_id$ represents the particular user for whom the feedback shall be calculated. Third, attribute $created\_at$ represents the date the assessment questionnaire was stored in the *TYT* database. Finally, the SQL command depicted at the bottom of Table II is used for calculating the patient feedback.

Prior to the feedback calculation (cf. Algorithm 2), the degree of reliability is determined by Algorithm 1. The decision which degree of reliability will be calculated by this algorithm is based on input parameter $correlation$. For example, if $correlation$ has value '$Stress$', the degree of reliability for category *stress* is calculated. Furthermore, input parameter $standardanswers$ is used. Note that parameters $loudness$ and $tocorrelatewith$ are important as they constitute the two dimensions the degree of reliability is calculated for. Following this, $tocorrelatewith$ may have values *mood, arousal, stress, concentration*. Based on these considerations, Algorithm 1 calculates the degree of reliability as follows (cf. Algorithm 1, Lines 17-29):

1) Sort array $loudness$ in ascending order.
2) Sort array $tocorrelatewith$ according to the ordering of $loudness$. To identify corresponding entries, the primary key of entity $standardanwers$ is used.
3) Split array $loudness$ into two subarrays of equal length. The first subarray comprises all loudness elements of $standardanswers$ with even index number; the second one, the elements with uneven index number.
4) Split array $tocorrelatewith$ into two arrays of equal length.
5) Note that Steps 1 to 4 became necessary to ensure that the variance among the subarrays is equal from a statistical point of view.
6) Calculate Pearson product-moment correlation coefficients (PCC) [13], [14][1]: The first PCC is calculated based on the first subarray of $loudness$ and the corresponding subarray of $tocorrelatewith$. The second PCC, in turn, is calculated based on the second subarray of $loudness$ and the corresponding subarray $tocorrelatewith$.
7) Normalize the results by adding 1 to both PCCs; i.e., ensure that the result of the next calculation will be between 0 and 1.
8) Evaluate which PCC has a higher value and divide the lower PCC by the higher PCC to ensure normalization. Note that the result of the division takes two PCCs into account and hence establishes the degree of reliability between arrays $loudness$ and $tocorrelatewith$.
9) Store division result to variable $dor \in [0, 1]$.

The scale to evaluate degree of reliability values is shown in Fig. 4③. Values below 0.6 indicate that not enough data for the respective category exist. Accordingly, the respective patient gets the feedback that not enough data has been gathered so far (cf. Fig. 3, Category *arousal*). In turn, values above 0.6 indicate that enough data has been

[1]PCC represents a common way to calculate a correlation of two sets.

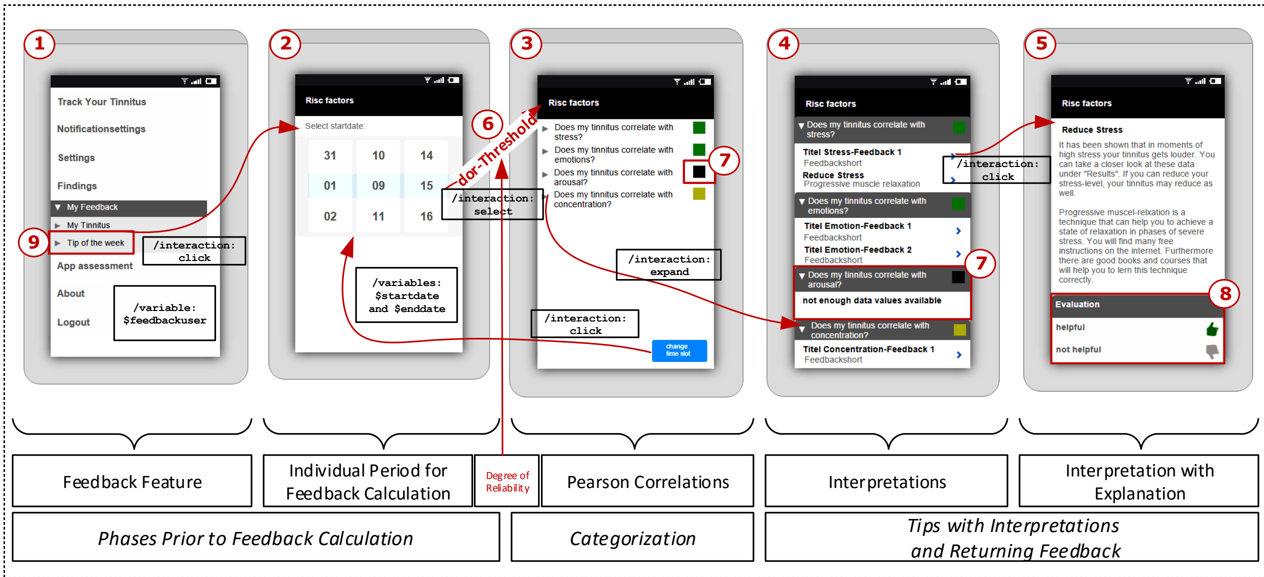

Figure 3: Patient Feedback Interaction

gathered. Altogether, first results indicate that the developed degree of reliability is appropriate for feedback calculation. Fig. 4 summarizes the basic steps for degree of reliability calculation. Algorithm 2, in turn, utilizes Algorithm 1 and assigns users to the four presented categories:

1) Load all relevant data from the database using the SQL command $SQLF$ (cf. Table II).
2) Calculate the four required degrees of reliability (*dors*) with Algorithm 2 (cf. Lines 4 to 7).
3) If at least one *dor* is above 0.6, start feedback calcu-ation (cf. Fig. 4②).
4) Calculate the PCCs for those categories with a *dor* above 0.6. Otherwise set the respective PCC to -1; i.e., return feedback to patients that not enough data has been gathered (cf. category *arousal* in Fig. 3).

Note that the evaluation of all patient data revealed that a least 15 assessment questionnaires need to be completed to be able to provide valuable feedback (cf. Algorithm 2, Line 3).

IV. Related Work

In general, mobile crowdsensing is an emerging research topic in various application domains [15], [16]. Interestingly, in the medical domain, mobile crowdsensing applications have been less proposed so far. One reason that the medical domain is less considered might be related to legal and data privacy issues [17]. However, using mobile crowdsensing in the medical context is promising [18], since mobile crowdsensing has unique features to gather valuable data [19]. In particular, mobile crowdsensing may gather context-aware [20] as well as daily life data [21] more effectively. Altogether, mobile crowdsensing is an emerging topic. The utilization of its possibilities, in turn, is still at the beginning.

Mobile systems offer also opportunities to measure behavioral or physiological data in daily life [22]. In this context, EMA approaches are considered to offer unprecedented

Algorithm 1: Algorithm for Degree of Reliability Calculation

```
Data:
$correlation: element of {mood,arousal,stress,concentration}
$standardanswers: array of two dimensions (1) loudness and (2) $correlation
Result:
dor: calculated dor for $correlation
begin
    loudness ←— standardanswers[0];
    dimension ←— 0;
    if $correlation = mood then
        dimension ←— 1;
    end
    else if $correlation = arousal then
        dimension ←— 2;
    end
    else if $correlation = stress then
        dimension ←— 3;
    end
    else if $correlation = concentration then
        dimension ←— 4;
    end
    tocorrelatewith ←— standardanswers[dimension];
    /* Split arrays loudness and tocorrelatewith into equal arrays
       comprising all elements with odd or uneven array indexes. Prior to
       splitting these arrays, two additional steps are required. First,
       array loudness is sorted in ascending order. Second, array
       tocorrelatewith is sorted corresponding to array loudness using
       the primary key of entity standardanswers.                      */
    split array loudness into two subarrays loudness_sa1, loudness_ss2 of equal
      length;                                                  /* sa=subarray */
    split array tocorrelatewith into two subarrays
      tocorrelatewith_sa1, tocorrelatewith_sa2 of equal length;
    /* Calculate Pearson product-moment correlation coefficients (PCC).
       Compare [13], [14] for required PCC formula.                    */
    corrValue1 ←—
      calculatePCC(loudness_sa1, tocorrelatewith_sa1);
    corrValue2 ←—
      calculatePCC(loudness_sa2, tocorrelatewith_sa2);
    /* Add 1 to corrValue1 and corrValue2. Hence, final dor is between
       0 and 1                                                          */
    corrValue1 ++;
    corrValue2 ++;
    dor ←— 0;
    if corrValue1 >= corrValue2 then
        dor ←— corrValue2/corrValue1;
    end
    else
        dor ←— corrValue1/corrValue2;
    end
end
```

Algorithm 2: Algorithm for Feedback Calculation

```
Data:
$feedbackuser: ID of patient for feedback calculation; SQLF: SQL-command (cf. Table II)
startdate, enddate: start and end date for feedback calculation provided by user
Result:
corrValues: array of correlation values (mood, arousal, stress, concentration)
begin
    /* use $feedbackuser, $startdate, $enddate in SQLF                          */
    standardanswers ⟵ SQLF;              /* multidimensional array */
    /* as a necessary prerequisite for calculating feedback, at least 15
       questionnaires must be processed by a patient                           */
    if sizeOf(standardanswers) > 14 then
        dor_mood ⟵ call Algorithm 1 with $standardanswers and
          $correlation = mood;
        dor_arousal ⟵ call Algorithm 1 with $standardanswers and
          $correlation = arousal;
        dor_stress ⟵ call Algorithm 1 with $standardanswers and
          $correlation = stress;
        dor_concentration ⟵ call Algorithm 1 with $standardanswers and
          $correlation = concentration;
        if dor_mood >= 0.6 or dor_arousal >= 0.6 or dor_stress >=
          0.6 or dor_concentration >= 0.6 then
            loudness ⟵ standardanswers[0];
            mood ⟵ standardanswers[1];
            stress ⟵ standardanswers[2];
            arousal ⟵ standardanswers[3];
            concentration ⟵ standardanswers[4];
            /* Calculate Pearson product-moment correlation coefficients
               (PCC). Compare [13], [14] for required PCC formula.     */
            if dor_mood >= 0.6 then
                corrValues[0] ⟵ calculatePCC(loudness, mood);
            else
                corrValues[0] ⟵ −1;
            end
            end
            if dor_stress >= 0.6 then
                corrValues[1] ⟵ calculatePCC(loudness, stress);
            else
                corrValues[1] ⟵ −1;
            end
            end
            if dor_arousal >= 0.6 then
                corrValues[2] ⟵
                  calculatePCC(loudness, arousal);
            else
                corrValues[2] ⟵ −1;
            end
            end
            if dor_concentration >= 0.6 then
                corrValues[3] ⟵
                  calculatePCC(loudness, concentration);
            else
                corrValues[3] ⟵ −1;
            end
            end
        end
    end
end
```

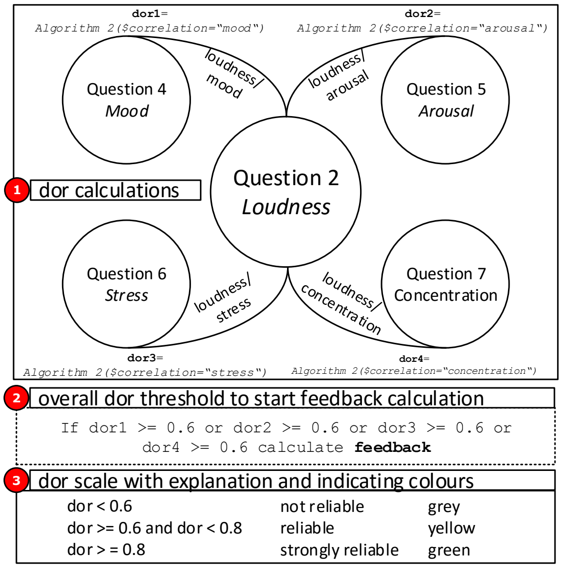

Figure 4: Degree of Reliability Calculation

opportunities to study neuropsychiatric symptoms under ecologically valid conditions [23]. Besides *TrackYourTinnitus*, two further studies, namely [24] as well as [25], presented EMA approaches to track tinnitus in daily life.

Moreover, there exist approaches enabling immediate mobile feedback based on personally gathered data. In general, data sensing with smart mobile devices offers new ways to support mobile users in various scenarios [5]. In the context of personalized healthcare, for example, many patients crave for immediate feedback. Furthermore, patients expect feedback directly provided to their smart mobile device [12], [26]. In this context, [27] presents a mobile application that provides patients with valuable information for their daily insulin dosages. Based on previous dosages, in combination with context data, the application indicates whether the current situation is similar to previously recorded situations. A broader perspective for combining personal data gathered with mobile devices with context information is presented in [28]. The latter describes feedback as a crucial incentive to increase patient motivation. Finally, [29] presents mobile applications that systematically measure vital signs enabling immediate feedback to users. Overall, the use of longitudinal patient data, gathered with a mobile crowdsensing service, for providing immediate feedback has been less considered by other approaches so far. To conclude, in various life domains, the feasibility of mobile crowdsensing has proven its usefulness. The medical field, albeit a highly promising application for mobile crowdsensing approaches, has been neglected so far.

V. Summary and Outlook

Using mobile crowdsensing offers promising perspectives for tinnitus assessment, therapy and research as well as for the medical field in general. With *TYT*, we obtained results that allow for totally new insights regarding tinnitus variability. The results further provide the basis for developing novel mobile crowdsensing services that foster tinnitus assessment, therapy, and research. In this context, we presented the patient feedback service we developed. In particular, we described a method to identify patient subgroups. Note that required data for such identification could not have been gathered without using mobile crowdsensing services.

The feedback service was integrated with the *TYT* backend as well as the Android mobile application. In future work, we will integrate the feedback service with the iOS mobile application as well. Furthermore, we will enhance the feedback service. We are working on techniques that allow medical experts to flexibly create feedback rules on their own. However, the feedback services already indicate that users are actually motivated to use this novel service. Notably, still more incentives and features are required to increase user motivation and hence to gather more valuable data on the tinnitus disease. In order to provide even more valuable feedback to users, medical experts as well as researchers are working on novel algorithms to automatically evaluate patient data. Altogether, over the next few years, mobile crowdsensing services will become increasingly important for collecting large and ecological valid longitudinal datasets in the context of clinical research.

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