Differences between Android and iOS Users of the TrackYourTinnitus Mobile Crowdsensing mHealth Platform

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***Abstract*—Presently, mHealth technology is often applied in the context of chronic diseases to gather data that may lead to new and valuable medical insights. As many aspects of chronic diseases are not completely understood, new data sources might be promising. mHealth technology may help in this context as it can be easily used in everyday life. Moreover, the bring your own device principle encourages many patients to use their smartphone to learn more about their disease. The less is known about a disorder (e.g., tinnitus), the more patients crave for new insights and opportunities. Despite the fact that existing mHealth technology like mobile crowdsensing has already gathered data that may help patients, in general, less is known whether and how data gathered with different mobile technologies may differ. In this context, one relevant aspect is the contribution of the mobile operating system itself. For example, are there differences between Android and iOS users that utilize the same mHealth technology for a disease. In the TrackYourTinnitus project, a mobile crowdsensing mHealth platform was developed to gather data for tinnitus patients in order to reveal new insights on this disorder with high economic and patient-related burdens. As many data sets were gathered during the last years that enable us to compare Android and iOS users, the work at hand compares characteristics of these users. Interesting insights like the one that Android users with tinnitus are significantly older than iOS users could be revealed by our study. However, more evaluations are necessary for TrackYourTinnitus in particular and mHealth technology in general to understand how smartphones affect the gathering of data on chronic diseases when using them in the large.**

***Keywords*-mHealth, Android, iOS, mobile crowdsensing, tinnitus, mobile data collection, chronic disease, chronic disorder**

I. Introduction

mHealth technology becomes increasingly important for many questions in healthcare. Chronic disorders are promising targets to apply mHealth technology to gather valuable data that can be used to find new insights for a disease or to develop new treatment methods. Especially smartphones are of utmost importance in this context as they can be easily utilized in everyday life. With regards to data collection, daily life data (e.g., self-reports and sensor data) can be gathered and may then be used to inform a user accordingly. Moreover, the daily life data gathered by smartphones could inform clinicians more accurately than retrospective self-reports of the patients [1]. Regarding treatment options, smartphones can be used to provide personalized self-help to patients and this might address several treatment barriers of chronic disorders. In general, mHealth tools like smartphones constitute a powerful way to empower patients in coping with their individual situation. Despite the promising opportunities, the use of mHealth technology for the aforementioned purposes is still in its infancy. In addition, mHealth technology comprises a very large field of different technologies. Mobile crowdsourcing or mobile crowdsensing are only two examples. Self-help mobile apps are further examples, which, in turn, also include a large variety of used methods. The latter vary from individually tailored diaries to mHealth intervention apps, which, for example, remind and instruct patients to do interventions if predefined context situations occur (e.g., heart rate level exceeds a predefined level).

Besides the variety of used mHealth technology, research in general is premature with respect to data that is gathered with it due to several reasons. First, it must be evaluated what data quality means in this context. Second, it must be considered whether or not existing evaluation methods fit to this kind of data. However, methods like Ecological Momentary Assessment (EMA; also known as: *ambulatory assessment & experience sampling*) have the potential to support clinicians in assessing symptoms or making diagnoses. In EMA, the variable in question (e.g., a symptom) is assessed repeatedly in daily life [2]. Third, it must be carefully evaluated how data is actually gathered. The latter includes how the collection procedure looks like, what smartphones are actually used, or whether patients are biased by issues arising through the use of the technology.

In this paper, we use the *TrackYourTinnitus* (TYT) mobile mHealth crowdsensing platform [3], [4] to gain insights whether differences between Android and iOS users can be observed. Note that the TYT mHealth mobile crowdsensing platform enables iOS and Android users to gather everyday life data with their own smartphones to understand their individual tinnitus situation better. Tinnitus can be described as the phantom perception of sound. Note that symptoms for tinnitus are subjective and vary over time. Therefore, TYT was developed to reveal insights on this patient variability. Moreover, depending on tinnitus definitions, the duration as well as on the patient age and birth cohort, between 5.1% and 42.7% of the population worldwide experience tinnitus at least once during their lifetime. By the use of EMA techniques, we aim at revealing new insights with regard to tinnitus [1], [5]. Thereby, prior to the results presented in this work, the evaluation of the gathered data already revealed valuable clinical insights [1], [6]. In addition, we have the goal in mind to identify the aspects how mobile crowdsensing can be also used for questions on other chronic disorders. Interestingly, with respect to Android and iOS users, we identified differences between these two user groups for TYT. These insights are presented in the work at hand and on top of the presented results, we raise questions that have to be taken into account for required technical TYT features in future. Furthermore, we discuss what questions related to the used mobile operating system should be considered when applying mobile crowdsensing technology in the context like we do.

Related work is discussed in Section II. In Section III, we briefly illustrate the mobile mHealth crowdsensing platform of TYT and explain the relevant issues when comparing Android and iOS users. Section IV presents the data and the statistics used for the juxtaposition of the Android and iOS users. In Section V, we present the results of the statistical analyses, which suggest that differences between the platform should be taken into consideration. Finally, a summary and an outlook are provided in Section VI.

II. Related Work

In this section, we discuss prior research on mobile crowdsensing, EMA, mHealth, and other works that directly compare Android and iOS users. Mobile crowdsensing has become an important research topic in various scenarios [7], [8]. However, mobile crowdsensing applications less exist in the medical domain although their use is promising for many questions [9]–[12]. One reason might be that many obstacles still exist or that they are less understood. On top of this, to maintain a mobile crowdsensing platform that is able to gather data with different mobile operating systems is a challenging endeavor.

In the context of EMA, other studies than TYT exist that use this method in the context of tinnitus [13], [14]. Moreover, further aspects are investigated using EMA approaches [15]–[18]. In general, EMA approaches are considered to offer unprecedented opportunities to study clinical symptoms under ecologically valid conditions [19], even though the utilization of its possibilities is still premature.

Regarding Android and iOS comparisons, related work that deals with peculiarities of the different mobile operating systems exists. In [20], such peculiarities are discussed for clinical interventions that are applied by the use of mobile applications. The authors describe that it costs quite a lot of time to cope with the different ways to develop mHealth applications. In addition, they state that it is naturally an interdisciplinary endeavor. However, data from iOS and Android users are not directly compared in this work. Another work discusses in an industrial setting how user interfaces on mobile devices can be developed and what aspects are crucial [21]. In this context, the used mobile operating systems as well as the applied development strategies are discussed for the development of user interfaces. The authors come to the conclusion that the development of a user interface is especially difficult for mobile devices. Again, no differences on mobile users for Android and iOS are presented. In the context of mobile data collection for medical purposes, related approaches exist that discuss peculiarities of different mobile operating systems for the data collection procedure [22]. However, user characteristics to distinguish, for example, iOS and Android users are not discussed. Finally, approaches that explicitly discuss peculiarities of mobile technology in the context of healthcare data exist [23], [24], which are closely related to the work at hand. They investigate methods for mobile technology that must be particularly taken into account in the context of mobile health. Again, a direct comparison of Android and iOS is not considered in these works.

In the context of this work, approaches that compare differences between Android and iOS in the context of mobile healthcare applications are of particular interest. In [25], [26], for example, security issues for Android and iOS mHealth applications are discussed. The authors of [27], in turn, discuss guidelines of Android and iOS to create applications that are able to support personal health records. In general, many works exist that aim to evaluate the differences and quality of mHealth applications that were developed for both mobile operating systems [28]–[30]. However, none of these approaches aim at a direct comparison of Android and iOS users that utilize the same mHealth platform or mHealth applications to cope with their individual health situation.

Approaches that focus on differences between Android and iOS users exist beyond healthcare questions [31]. Android and iOS users were directly compared only in a few studies [32]–[34]. These studies have found that iOS users are more likely female, in the mid-30s, with a graduate degree, in a higher income group, with more technology knowledge, and that iOS users spend more time using applications than Android users. Clinically relevant differences were reported in [32] for the SmokeFree28 (SF28) application. For example, iOS users downloaded the app more likely for a serious attempt to quit smoking or Android users took stop-smoking medication more often. Another study investigated whether iOS and Android users differ in personality traits [35]. Only a few and small differences were found. Altogether, research on mobile health and the differences between Android and iOS users are still in their infancy.

III. Material and Methods

TrackYourTinnitus (TYT) is a mobile crowdsensing [7] mHealth platform, which is build on four components. First, it offers a website for user registration and other user-related features (e.g., data visualization). Second, it offers an Android and iOS application. Third, a MySQL database is used for the central repository for the data collected [4]. Fourth, a RESTful API is provided that enables the communication between the mobile applications, the website, and the database. In general, TYT was developed to track the individual tinnitus of its registered users. The tracking is based on a set of existing and individually developed questionnaires. In addition, the environmental sound level can be measured when tracking the users. Due to the lack of space, we refer to [4] for technical insights on TYT. In addition, a detailed description of the data collection procedure of TYT can be found in [5].

For the comparison of Android and iOS users, we briefly share relevant facts about the TYT platform in this section. First of all, the procedure depicted in Fig. 1 is accomplished by all TYT users.[1] Thereby, TYT pursues three goals. First, data shall be collected on a daily basis (cf. Fig. 1, 4). However, a crowd user shall not foresee the times he or she is asked to sense data. This is ensured by asking the crowd users in various daily life situations (cf. Fig. 1, 3). Second, the collected data shall enable new kinds of data analytics like juxtaposing real-time assessments and retrospective reports [5] (cf. Fig. 1, 2&4). Third, gathered data shall be used to provide feedback to the mobile crowd users. From the perspective of TYT users, they first have to register (cf. Fig. 1, 1). This can be accomplished by using the website, the Android or the iOS application. During the registration procedure, we automatically identify the used mobile operating system. If a user registers through the website, then we obtain the used mobile operating system in further steps. However, in the latter case, the user gets an empty field in the database for the mobile operating system during the register procedure. Note that these mobile users are excluded from this study. Then, users must fill in questionnaires (cf. Fig. 1, 2). For example, they have to provide demographic data and fill in the "Mini-TQ-12" questionnaire [36], which measures tinnitus-related psychological problems. Altogether, the completion of the questionnaires is a fundamental prerequisite for users who want to use the features of the continuous mobile crowdsensing (cf. Fig. 1; Steps 3 and 4).

In this paper, data related to Steps 1 and 2 were analyzed. More specifically, we compared data provided in Step 2 with the information what mobile operating system has been identified during Step 1. As Step 2 identifies important aspects about the individual tinnitus situation, we conducted this study with the question in mind to reveal whether or not users that register to the TYT platform with an Android smartphone differ in their tinnitus characteristics from the ones that register with an iOS smartphone. To answer this question, we used the entire data source of existing TYT users. More precisely, TYT presently has 3122 registered users. For the work at hand, the following users had to be excluded:

- Users that registered through the website.
- Users for which the used mobile operating system could not be certainly identified.

In total, we had to exclude 1.605 users. That means, 1.517 users were included in the presented data analysis. Moreover, one more important aspect must be briefly mentioned. Both mobile applications were developed following the *native development approach*; i.e., solely using Objective-C and Java to develop the applications. Furthermore, no frameworks were used and much efforts were done to create similar user interfaces for both mobile applications. In addition, we involved domain experts when developing the mobile applications. Fig. 2 shows one part of the same questionnaires on iOS and Android.

IV. Data and Statistics

The current analysis relies on an export of the TYT database made in February 2018. All users were exported and test users were excluded. All statistical analyses were performed with SPSS 25. Frequencies (n), percentages (%), means (M), and standard deviations (SD) were calculated as descriptive statistics. To compare users registering with the iOS operation system and users registering with the Android operation system, *Chi-squared tests* were used for categorical variables and *t-tests* for independent samples were performed for numeric variables. All statistical tests were conducted two-tailed and the significance value was set to $p < .05$.

V. Results

The number (February 2018) of registered users with available information on the mobile operating system used during the registration amounts to $n = 1.517$ users. This is the total sample for the current study. Most of these users come from Germany ($n = 536; 35.3\%$), the United States ($n = 210; 13.8\%$), the United Kingdom ($n = 83; 5.5\%$), and the Netherlands ($n = 79; 5.2\%$). Of the total sample, $n = 819$ used iOS to register (54.0%), and $n = 698$

[1] More detailed information about the procedure can be found at https://www.trackyourtinnitus.org/process.pdf

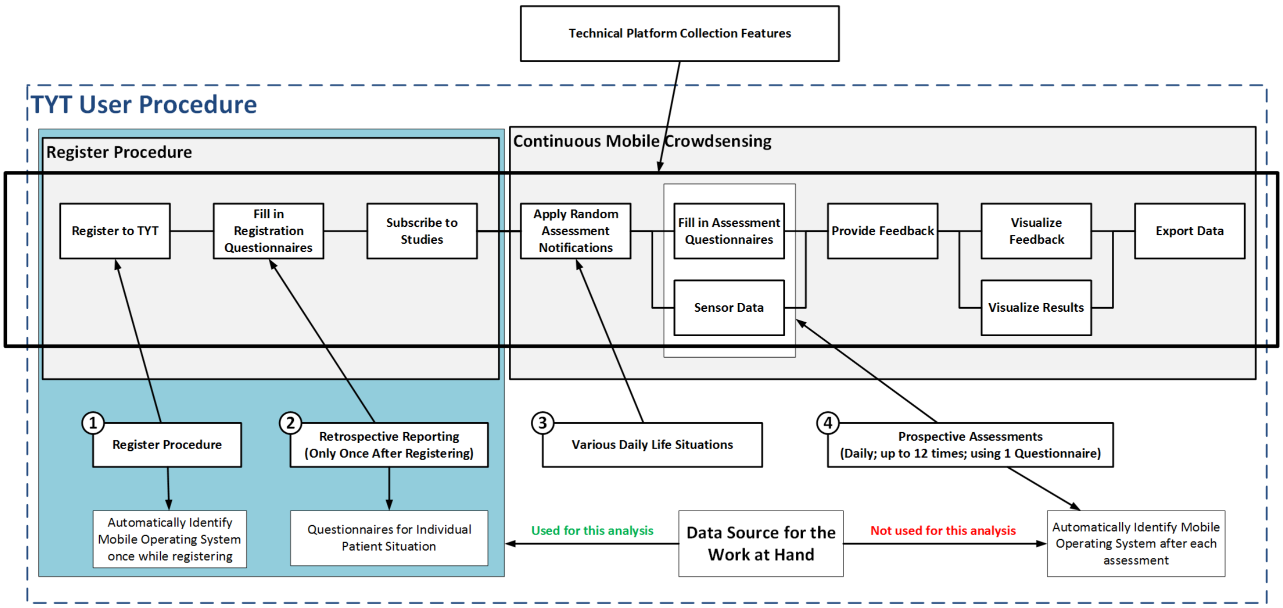

Figure 1: TYT Mobile Crowdsensing Collection Procedure

	iOS Users	Android Users	
	$n(\%)$	$n(\%)$	*Test Statistics*
Gender (n=781 iOS; n=687 Android)			$\chi^2(1) = .94, p = .331$
Female	227 (29.1)	184 (26.8)	
Male	554 (70.9)	503 (73.2)	
Self-reported Tinnitus Variability (n=776 iOS; n=680 Android)			$\chi^2(1) = .45, p = .501$
No	208 (26.8)	193 (28.4)	
Yes	568 (73.2)	487 (71.6)	
Self-reported Family History of Tinnitus (n=779 iOS; n=685 Android)			$\chi^2(1) = .02, p = .889$
No	587 (75.4)	514 (75.0)	
Yes	192 (24.6)	171 (25.0)	
Self-reported Causes of Tinnitus Onset (n=782 iOS; n=681 Android)			$\chi^2(1) = 8.81, p = .117$
Loud Blast of Sound	150 (19.2)	104 (15.3)	
Whiplash	26 (3.3)	15 (2.2)	
Changes in Hearing	94 (12.0)	73 (10.7)	
Stress	222 (28.4)	195 (28.6)	
Head Trauma	29 (3.7	28 (4.1)	
Other	261 (33.4)	266 (39.1)	
	M(SD)	*M(SD)*	
Age (n=752 iOS; n=693 Android)	42.63 (13.13)	44.11 (13.41)	$t(1443) = -2.11, p = .035$
Self-Reported Tinnitus Duration (n=772 iOS; n=673 Android)	7.21 (9.51)	11.20 (12.97)	$t(1216.68) = -6.72, p < .001$
Tinnitus-Related Psychological Distress (Mini-TQ) (n=782 iOS; n=697 Android)	14.01 (5.94)	13.64 (6.21)	$t(1477) = 1.19, p = .233$

Table I: Comparisons between TrackYourTinnitus Users Registering with the iOS vs. Users Registering with the Android Operating System.

registered with Android (46.0%). The results of the comparisons between iOS and Android users are summarized in Table I: Android users were significantly older ($p = .035$) and had a significantly longer self-reported tinnitus duration ($p < .001$) than iOS users. Yet, both groups did not differ in tinnitus-related psychological distress as the values of the Mini-Tinnitus Questionnaire [36] were not significantly different between iOS and Android users ($p = .233$). Moreover, neither gender ($p = .331$), nor self-reported tinnitus variability ($p = .501$), nor self-reported causes of tinnitus onset ($p = .117$), nor self-reported family history of tinnitus ($p = .889$) differed between iOS and Android users.

VI. Summary and Outlook

This paper presented results of a data analysis that compared differences of Android and iOS users of the TYT mHealth crowdsensing platform. Interestingly, very little empirical work exists that compared such differences in the context of mHealth gathered data. Contrary to the Android vs. iOS comparison of the SF28 application [32], we found no differences in gender but in age. In general, based on results of this study, differences between Android and iOS users can be beneficially taken into account from the technical as well as the medical perspective. Technically, if Android users are older than iOS users, it might be one direction to use this information to further work on the user interface of Android. For example, by taking the age into consideration, the user interface can be adjusted to the age. As older people perceive the color blue [37] poorer compared to younger people, this color can be less used for older people. The other significant result was that Android users had a longer duration of the self-reported tinnitus than iOS users. Yet, it should be kept in mind that tinnitus duration and age are correlated, since older patients will have a higher chance to have more years since onset than younger ones. A limitation of the current study is related to

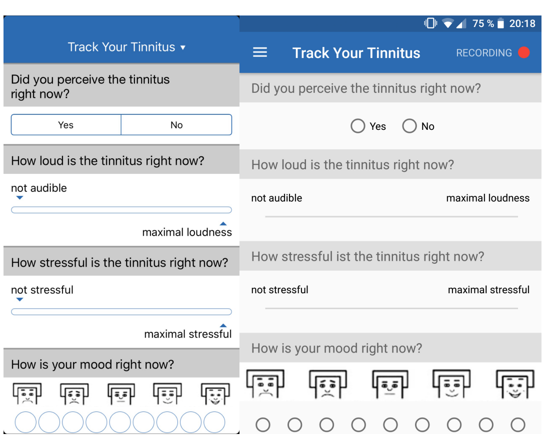

Figure 2: Same Questionnaire on iOS (left) and Android (right)

the fact that out of the total user population, only around 50% could be analyzed because of missing information on the operating system. This limits the generalizability of the results. Therefore, more studies are needed to investigate whether the results can be replicated. In future work, we plan to integrate more items to our applied questionnaires that enable more in-depth analyses on the user characteristics. For example, a question could be added that asks the user whether or not he or she particularly prefers the identified mobile operating system. If this question is answered positively, another questions could be what are the reasons for this preference. Overall, for TYT, it seems that a comparison between Android and iOS users is promising for further technical developments as well as analyses that reveal new insights for the domain experts. As a next step for TYT, we will analyze TYT data that was gathered during the continuous mobile crowdsensing procedure with respect to differences between Android and iOS users. Thereby, we additionally aim at questions like whether users change their mobile operating system while providing data to TYT. Furthermore, another interesting question is to combine the analysis with the country users come from. Altogether, many questions and opportunities arise for TYT when comparing Android and iOS users. If the presented results for TYT can be generalized to other mHealth platforms or solutions is still an open question that should be dealt with in future work. However, as such comparisons might provide new and valuable results, it should be generally considered in the context of mHealth gathered data.

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