Predicting the Perception of Tinnitus based on Daily Life Data of the TrackYourTinnitus mHealth Platform in Combination with Country Origin and Season

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ABSTRACT

Tinnitus is a phantom auditory perception in the absence of external sound stimulations. The chronic perception of tinnitus can severely impact the quality of life in those that suffer from it. As tinnitus is characterized by a heterogeneity of the patient's symptoms, researchers often use a multi-modal data fusion approach, i.e., they combine tinnitus data with other data source, to reveal new insights. In the context of differences across countries and seasons based on mobile health data, less insights have been presented so far. Therefore, data of the TrackYourTinnitus mHealth platform (TYT) were investigated to see whether season-related differences in the symptom profiles of TYT users exist. In addition, differences based on the country origin of TYT users were investigated. The conducted analyses address three major research questions. First, it was analyzed whether the `momentary tinnitus` measured by daily answers of TYT users can be related to the season or their country origin. To do so, a gradient boosting machine (gbm) from the field of machine learning was trained and analyzed with the goal to classify the `momentary tinnitus`. Based on the used features, the `momentary tinnitus` could be classified with an accuracy of 94.03% on the daily assessment level, indicating differences in tinnitus of TYT users with respect to the season and country origin. Second, another gbm was trained to regress the `tinnitus loudness` on a scale from 0 to 100. On the daily assessment level, the `tinnitus loudness` can be regressed with a mean absolute error rate of 7.9 %-points. Third, on top of the machine learning analyses, country- and season-specific differences were analyzed in the light of further perspectives. For example, it could be revealed that tinnitus varies with the temperature in certain countries. The considered perspectives, in turn, have been derived through the inspection of the TYT data set and its possibilities. The presented results show that the season and the country origin seem to be valuable features when being combined with longitudinal mHealth data of tinnitus patients on the daily assessment level.

Introduction

Tinnitus is widely known as a long-term noise in the ears, which is described by patients through heterogeneous sound manifestations[1]. Economically, tinnitus induces a high burden, as about 10 - 15% of the worldwide population[2,3] is affected by this chronic disorder. 2.4% of these affected patients severely suffer from tinnitus day by day[4], while one to two percent experience a reduction in their quality of life due to tinnitus, including insomnia, anxiety, hearing difficulties, or depression[5–7]. At present, no general treatment exists, which is able to effectively reduce `tinnitus loudness` and related fluctuations. Consequently, many patients are confronted with a complex healthcare situation, which often reduces the quality of life significantly. The mentioned heterogeneity of tinnitus symptoms also complicates the development of new and more general treatment methods[8,9]. However, on an individual basis, tinnitus can be reduced, for example, by the use of cognitive behavioral therapies[10].

Various efforts are constantly made to learn more about the heterogeneity of symptom profiles of tinnitus patients. However, data sources are often missing to investigate aspects with respect to this heterogeneity of symptom profiles that seem to be interesting. As the proliferation of smartphones has led to powerful mobile health solutions (denoted as mHealth solutions) that are able to establish data sources with opportunities to better deal with differences of symptom profiles, in this paper, such mHealth data source is investigated for tinnitus patients. Although respective investigations have gained attention recently, many opportunities are still not utilized. For example, a comparison of mHealth data of tinnitus users across countries does not

exist to the best of our knowledge. In addition, detailed insights based on season differences are also less considered in the context of collected mHealth tinnitus data so far. Therefore, these two questions on differences across seasons and the country origin have been selected for further investigations on symptom profiles of tinnitus patients using a mHealth platform.

In the context of the mentioned differences, only little research has been presented. In addition, these presented works are all beyond the scope of mHealth. There is one study on seasonal changes in tinnitus symptomatology, which concludes that searches for tinnitus aspects are higher in winter than in summer in some countries[11]. Another work suggests an association of depression and season. It provides Internet-based evidence for the epidemiology of seasonal depression. The results suggest that Internet searches for depression by people at higher latitudes are more affected by seasonal changes, while this phenomenon is faded out in tropical areas[12]. However, already more than 70 years ago, it was clinically observed that tinnitus increases during the winter months[13,14]. Seasonal affective disorders (SAD), in turn, were studied by the authors of[15]. They conclude that Seasonal affective disorders are present when a symptom occurs during the winter months and disappear completely in summer.

When aiming at mHealth solutions to investigate these differences, at first, the type of collected data must be taken into account as mHealth solutions can be based on different methods, strategies and concepts. In this work, Ecological Momentary Assessments (EMAs) are the basis for the investigations as they are particularly appropriate for the investigations at question[16]. However, EMA only defines the strategy how participants of a study (usually, longitudinal studies) will be questioned. Three aspects are the main pillars of the EMA strategy: EMAs must be carried out in real life (opposed to a clinical environment) and at arbitrary points in time (to capture the moment of a participant). Third, a concrete measurement (e.g., though a questionnaire) must be accomplished. If EMAs are now performed through the boundaries of a year and across countries, a data source can be established through such measurements that enables a powerful basis to investigate country- and season-specific differences. Recall that EMA only defines the strategy. In the context of mHealth, digital phenotyping techniques[17] express an important trend to use smartphones to practically enable Ecological Momentary Assessments (EMAs). Digital phenotyping quantifies the human phenotype in a moment-to-moment fashion using active and passive data from mobile devices. As smartphones are present in daily life of almost anyone, the performance of EMAs through smartphones can effectively capture the daily life of users over time. Respective evaluations based on mHealth data, in turn, have been recognized as potential alleys for a better support of patients[18]. mHealth apps, in turn, are the major instrument to operationalize digital phenotyping and EMAs. Many mHealth apps have been presented in this context[19–21]. Although valuable data sources have been established by the use of digital phenotyping, mHealth data comes also with drawbacks[22], which must be considered carefully. For example, in EMA settings, in which users fill out several questionnaires each day over a longer period of time, it must be ensured that the data was provided in a meaningful way. To get a better impression regarding the meaningfulness, the following example shows emerging challenges through EMA. If users have to fill out a lot of questionnaires through EMAs more than once a day, then they could tend to fill out only to accomplish the task itself, without providing the actual momentary situation.

In the context of tinnitus, the TrackYourTinnitus platform (TYT), which is based on mobile crowdsensing techniques[23] as well as EMAs[24], puts digital phenotyping into practice. Crowdsensing, in turn, connects a group of people, who have mobile devices with sensing and computing capabilities, collectively sharing data, and extracting information to measure, map, analyze, and estimate any processes of common interest. TYT was initially developed to investigate questions about the aforementioned heterogeneity of symptom profiles of tinnitus patients[21,25,26]. The procedure how users are walking through TYT is described in[27]. In essence, users register to the platform (website or mobile apps), then they have to fill out three baseline questionnaires asking about demographic data and tinnitus characteristics. The users have to fill out these questionnaires before they are able to start with the EMA procedure. The latter is applied through two native apps, which are available for iOS and Android in the official app stores. The EMA procedure consists of a daily questionnaire with eight questions. This questionnaire is applied using two strategies. The first one is based on the idea that users can fill out the questionnaire whenever they want. The second strategy is based on notifications. Up to 12 random notifications or a fixed schema are used (can be chosen by users, which schema they prefer) to remind the users to fill out the EMA questionnaire. The mainly used schema are the random notifications. As this selection follows the idea of in situ measurements in the sense of digital phenotyping, many investigations and analyses become possible. Of further importance, until today, this setting has motivated over 8000 users from all parts of the world to provide more than 100,000 questionnaires. The use of mHealth in this context, apart from TYT, has been proposed by many other mHealth projects[10,28,29], which indicates that strategies like EMA or digital phenotyping are promising in the context of tinnitus research.

The mentioned investigations on differences across seasons and the country origin have been identified to be possible on the TYT data source. For the concrete analyzes, we have decided to work on the following three major research questions (RQ):

- RQ1: Can the `momentary tinnitus` (Question 1 of the daily EMA questionnaire; yes/no question) of TYT users be predicted (i.e., a binary classifier be trained using machine learning based classifiers) using the features country, season, age, and sex as well as the daily EMA questionnaire and its questions on mood, arousal, stress, concentration, and the worst symptom perception?

- RQ2: Can the reported loudness of TYT users (Question 2 of the daily EMA questionnaire; slider question) be predicted (i.e., a regressor be trained using machine learning based classifiers) based on the same features like for RQ1?
- RQ3: Are we able to reveal (based on descriptive statistics) country- and season-specific differences for the reported `momentary tinnitus` based on the daily EMA questionnaires of TYT users?

Regarding RQ1 and RQ2, we will present results from two machine learning analysis. As TYT was able to gather more than 100,000 EMA questionnaires since 2013, which are comprised of many dimensions, we decided to answer RQ1 and RQ2 based on machine learning algorithms. As we already revealed interesting results on TYT EMA-data based on machine learning[30] as well as the use of machine learning has been generally recognized in the context of mHealth data in the last years with much attention and valuable results[31–34], the following paper links up with these findings.

Regarding RQ3, we will present descriptive statistics about the identified country- and season-specific differences. We have detailed the research question into four sub-questions due to the following reason: Based on the two main goals to investigate country- and season-specific, which represent the two categories of differences, we were able to derive further promising questions. $RQ3_3$ is a combined perspective of the country and the season, while $RQ3_4$ is inspired by medical experts. The following list presents the four sub-questions:

i $RQ3_1$: Are there country-specific differences for the `momentary tinnitus`?

ii $RQ3_2$: Are there season-specific differences for the `momentary tinnitus`?

iii $RQ3_3$: In the light of a combination of country- and season-specific differences, the question arose, whether the `momentary tinnitus` varies within the year and across countries.

iv $RQ3_4$: The question arose, whether country- and season-specific differences of the reported worst symptom can be identified.

Three additional notes are important regarding $RQ3_1$-$RQ3_4$. First, the last sub-question was set up due to the involved medical experts as severe symptoms play an important role in the context of tinnitus research. As TYT asks about nine possible worst symptoms, we investigated how the worst symptom differs across countries and seasons. As the combined perspective taken for $RQ3_3$ was useful, this combined perspective was also accomplished for $RQ3_4$. Second, in the context of season-specific differences, we added an additional dimension, the temperature course throughout the year, which is inspired by the results of[12].

Finally, for the prediction tasks in RQ1 and RQ2, we excluded features of TYT that are highly correlated with the target, such as `tinnitus loudness`, `tinnitus stress`, and `momentary tinnitus`. However, we included features that are known to be correlated with tinnitus, such as sex and age[35].

Materials and Methods

The study was approved by the Ethics Committee of the University Clinic of Regensburg (ethical approval No. 15-101-0204). All users read and approved the informed consent before participating in the study. The study was carried out in accordance with relevant guidelines and regulations.

The questionnaires. For the tinnitus prediction task, three linked data sets were used. The first one refers to the baseline questionnaire named *Tinnitus Sample Case History Questionnaire (TSCHQ)*. This questionnaire is completed by each TYT user *once* when starting the app for the fist time. In this questionnaire, demographic data as well as data about the individual course of the tinnitus are collected, such as the onset of the tinnitus, or the worst symptom that is related to tinnitus. Baseline characteristics from this questionnaire for the five countries (CH, DE, GB, NL, US), as well as all other countries, can be seen in Table 4. These five countries are the subject of RQ3. For the characteristics *handedness* and *family history of tinnitus complaints*, a χ^2 test was performed. The χ^2 test showed that there was no significant association within the country groups, $\chi^2(8, N=2319) = 6.64$, p=0.58 for *handedness*, and $\chi^2(4, N=2314) = 4.33$, p=0.36, for *family history*. To compare the age distributions between the countries, a one-way ANOVA was performed with $F(4, 2267) = 5.17$, $p < 0.001$. A post-hoc pairwise Tukey test revealed differences between DE and US (mean diff. = 2.36, $p < 0.05$), and GB and US (mean diff. = 5.07, $p < 0.01$). The remaining eight pairwise groups had no significant differences in their means.

When logging in into the TYT platform, users are asked for their worst tinnitus symptom. This symptom can be one of the following.

- I am feeling depressed because of the tinnitus.
- I find it harder to relax because of the tinnitus.
- I have strong worries because of the tinnitus.
- Because of the tinnitus it is difficult to follow a conversation, a piece of music or a film.
- Because of the tinnitus it is hard for me to get to sleep.
- Because of the tinnitus it is difficult to concentrate.
- Because of the tinnitus I am more irritable with my family, friends and colleagues.
- Because of the tinnitus I am more sensitive to environmental noises.
- I don't have any of these symptoms.

As we also record fill-in dates of answers to this questionnaire, and the country of the user, we can link the worst symptom to both the season and country. To assign the fill-in date to a season, we used the astronomical seasons as a guide. More specifically, spring starts in March 21st, summer in June 21st, autumn in September 23rd, and winter in December 21st. For countries of the southern hemisphere, the seasons are opposite, i.e. spring becomes autumn, summer becomes winter. etc. 3.2 % of the collected data comes from countries in the southern hemisphere. The correction of the seasons concerns only the analysis for the worst symptom. For the machine learning part, countries in the southern hemisphere were not involved due to the insufficient number of completed questionnaires.

The second data set refers to the *daily questionnaire*. It includes eight questions about the current tinnitus state, i.e., the tinnitus situation and the feelings of the individual *right now*. However, the eighth *dynamic* question depends on the worst symptom of the individual from the TSCHQ questionnaire and asks whether the individual has this specific worst symptom right now or not. If an individual answered *I don't have any of these symptoms* in the beginning, no eighth question appears in the daily questionnaire. Consequently, the number of data for question 8 depends on the number of individuals that have selected this worst symptom in questionnaire TSCHQ. On the other hand, the number of answers for questions one to seven equals each other. These questions are seen by every individual in the same way and are as follows:

1. Did you perceive the tinnitus right now?
2. How loud is the tinnitus right now?
3. How stressful is the tinnitus right now?
4. How is your mood right now?
5. How is your arousal right now?
6. Do you feel stressed right now?
7. How much did you concentrate on the things you are doing right now?
8. *This question depends on the worst symptom selected in the questionnaire TSCHQ.*

Depending on the features that are selected for the classification task, the number of examples m depends on the dynamic question eight. The questions for *mood* and *arousal* are questions using a self-assessment scale (SAM)[27], with 9 possible values. Depending on a user's operating system, the answer is stored with different accuracy. Therefore, rounding errors can occur in the hundredths range on Android phones. We neglected these rounding errors in pre-processing considering the amount of 18 other features (`countries`, `seasons`, `sex`, `age`, `mood`, `arousal`, `stress`, `concentration`, `worst symptom perception`), as described in Table 1.

Data preprocessing

The raw data comes from three .csv files, which, in turn, are extractions from the TYT database. The first file is a dataframe containing meta information from all registered users (number of users = 8685 by Feb. 2021). This meta data includes, among others, the country, nationality, and mobile platform. The second file is the baseline questionnaire and contains 3700 users that filled out the initial questionnaire. The daily questionnaire is the last file with 3044 users that answered 98,074 daily questionnaires. We can see from this, that of the registered users, about one in three completes the daily questionnaire at least once.

The `user_id` is mandatory to merge the three data sets. As a consequence, all rows where `user_id` equals `NULL`, we dropped that row. We further removed the 25 test-users with known user IDs to reduce bias and noise in the data. The remaining merged dataframe had 97,742 rows and 65 columns. This dataframe has been used for the statistical analyses provided in the results section.

Machine Learning Preprocessing For the machine learning task, a further preprocessing was required. Gradient boosting machines can only handle numerical data with no missing values. We therefore dropped rows that contained missing values, which affected about 24 % of the data. We then needed to convert categorical features into numbers. As decision trees split data in binary groups, we used the `pandas.get_dummies()` method to convert the countries and seasons into several columns. The column name is then the category. A `1` indicates that this category applies, i.e., `autumn = 1`, which, in turn, means that

the other seasons must be zero. In order not to increase the number of columns unnecessarily, we used the `drop_first = True` keyword argument. This means, we get k-1 dummies out of k categorical levels by removing the first level. The last step considered the imbalanced distribution of the target variable *tinnitus occurrence*. About 79 % of the users reported *yes*. Any naive machine learning classifier would therefore simply always predict *yes*, regardless of the input of features and would still get 79 % accuracy on average. Using the F1 accuracy score, the performance can be measured better, but the classifier would still be over-trained on positive examples. We therefore bootstrapped negative examples with replacement until we had a balanced dataset. The final dataset had 118,054 samples with 22 features each.

variable_name	variable meaning	mean	std	scaling
AT	Austria	0.02	0.13	
CA	Canada	0.03	0.16	
CH	Switzerland	0.08	0.27	
DE	Germany	0.62	0.49	
GB	Great Britain	0.05	0.21	
IT	Italy	0.01	0.10	
NL	Netherlands	0.07	0.25	
NO	Norway	0.02	0.13	binary
RU	Russia	0.02	0.14	
US	United States	0.09	0.29	
spring		0.26	0.44	
summer	season	0.24	0.43	
autumn		0.25	0.43	
winter		0.25	0.44	
Male	Sex	0.74	0.44	
age	Age in years	49.71	12.98	integer
question4	How is your mood right now?	0.58	0.20	SAM from 0 to 1 with stepsize 0.125
question5	How is your arousal right now?	0.25	0.22	
question6	Do you feel stressed right now?	0.26	0.23	Slider in range (0, 1)
question7	How much did you concentrate on the things you are doing right now?	0.59	0.31	
question1	Did you perceive the tinnitus right now?	0.50	0.50	binary
question2	How loud is the tinnitus right now?	0.47	0.30	Slider in range (0, 1)

Table 1. Overview of the features and the targets used to train the gradient boosting machines for RQ1 and RQ2. Most of the features are binary, `age` has the highest cardinality. The whole dataset had the shape (118054, 22). For the ML feature, the average `age` is higher as some users completed the questionnaire over several years and`age` was calculated at the time of completing the daily questionnaire.

Estimation of feature importances. The values of Table 2 were calculated using three different methods, the Gini importance, the permutation importance, and the correlation metric. Depending on the feature scaling, two different correlation metrics have been applied. If the input feature was categorical, Corrected Cramer's V[36] was applied. If it was continuous, the Point Biserial method[37] was used. Cramer's V is defined in range (0, 1), whereas the Point Biserial correlation is defined in range (-1, 1). Nevertheless, to be able to order the results *within* the column, we took the absolute value from the Point Biserial result. Although all results are in percentages, it is not possible to compare them line by line. This is due to the different units of measurement. Therefore, we have created the ranking. For the Gini and the permutation importances, both methods are used using the trained gradient boosting machine. The Gini importance is an impurity-based method. The higher it is, the more

important the feature is. Notably, within this column, all values add up to 100 %. The importance of a feature is calculated as the reduction of the impurity caused by this feature. For the permutation importance, the percentage values are an estimate for the increase of the error rate on average, if that features would have been replaced by a random feature. That means, if the variable `gender` would be replaced with a random variable, the error would increase by 6.43 %-points. That column does not necessarily add up to 100 %.

Gradient Boosting Machines for classification of `momentary tinnitus` and regression of `tinnitus loudness`

Why did we chose the Gradient Boosting machine? It is a tree-based Machine Learning algorithm and related to Random Forests. Machine Learning contests on the Kaggle platform have recently shown that this algorithm is superior to most state-of-the-art Deep Learning methods when it comes to tabular data, such as house pricing prediction problems. Both, Random Forests and Gradient Boosting Machines use several trees to predict the outcome. However, one of the main differences between those two algorithms is the *time aspect*. That is, the Gradient Boosting algorithm learns from previous miss-classified samples by putting more weight on those. Furthermore, it does not easily tend to overfitting like decision trees do.

We used the Python implementation from scikit-learn[38] to apply the Gradient Boosting machine to the dataset. We then defined the 20 features (10 countries, 4 seasons, sex, age, mood, arousal, stress, concentration level) and the targets (`momentary tinnitus, tinnitus loudness`. The whole dataset was divided into three sets: Training, development, and testing. Training plus development got 70 % of the data, testing 30 %. To avoid a selection bias within the classification problem, we stratified on *y*. Setting a `random_state` (also known as seed) ensured that the results are reproducible. For the tuning of the hyperparameters, we used a gridsearch approach. Within that, we varied the `learning_rate`, the `max_depth` of each tree, the sizes of the `subsample`s, the minimum number of samples per leaf, and the fraction of randomly chosen features per tree. 1,280 combinations of the hyperparameters have been evaluated systematically, the final chosen setup can be seen in Listing 1 for the classifier and Listing 2 for the regressor, respectively. Each combination was cross-validated within the training set using a 5-fold split. This means that the 70 % of the training data was further divided into 5 folds. Four of each were used for training and one for validation.

For the classification task, the mean test accuracy score on validation was 91.1 % (std = .002). On the test dataset, an even higher accuracy of **94.03 %** was achieved.

When leaving out the features `sex` and `age`, the mean test score dropped to 88.9 % using the same hyperparameters. Using only the binary features `seasons` and `countries` leads to a decrease of the accuracy on the test set down to 58 %. This is caused by the low dimensional feature space.

For the regression task, a mean absolute error of 8.1 % was achieved on the validation set (std = .0006) and a **7.9 %** error on the test set.

```
# Gridsearch setup
params_gb = {'learning_rate': [0.1, 0.2, 0.3,
    0.5, 1],
             'max_depth': [3, 4, 5, 10],
             'verbose': [1],
             'random_state' : [42],
             'subsample': [0.25, 0.5, 0.75, 1],
             'min_samples_leaf': [1, 2, 3, 10],
             'max_features': [0.25, .5, .75, 1]
             }

# Chosen hyperparameters
GradientBoostingClassifier(loss='deviance',
    learning_rate=0.5, n_estimators=100,
    subsample=1.0, criterion='friedman_mse',
    min_samples_split=2, min_samples_leaf=1,
    min_weight_fraction_leaf=0.0, max_depth=10,
    min_impurity_decrease=0.0,
    min_impurity_split=None, init=None,
    random_state=42, max_features=0.5, verbose
    =0, max_leaf_nodes=None, warm_start=False,
    validation_fraction=0.1, n_iter_no_change=
    None, tol=0.0001, ccp_alpha=0.0)
```

Listing 1. Hyperparameter set up for the Gradient boosting classifier

```
# Gridsearch setup
params_gb = {'learning_rate': [0.1, 0.2, 0.3,
    0.5, 1],
             'max_depth': [3, 4, 5, 10],
             'max_features': [0.25, .5, .75, 1],
             'random_state' : [42],
             'subsample': [0.25, 0.5, 0.75, 1]
             'verbose': [1]
             }

# Chosen hyperparameters
GradientBoostingRegressor(learning_rate=0.5,
    max_depth=10, max_features=0.75,
                          random_state=42,
                              subsample=1,
                              verbose=1)
```

Listing 2. Hyperparameter set up for the Gradient boosting regressor

Results

In this section, the results for the research questions are presented subsequently. At first, we focus on the first question of the daily TYT questionnaire (*Did you perceive the tinnitus right now?*). We refer to this question as the `momentary tinnitus`

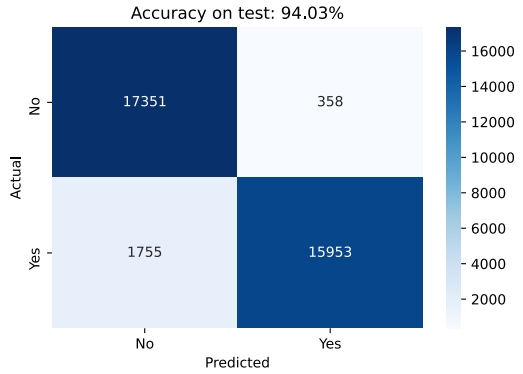
in the following. Second, we consider the `tinnitus loudness` (*How loud is your tinnitus right now?*) and refer to this question as `tinnitus loudness`. Third, we analyze these two targets `momentary tinnitus` and `tinnitus loudness` in a global context by relating them to the country, season, and temperature.

Features for RQ1 and RQ2. We used four different groups of features. The first group of features are dummy features indicating whether an individual comes from that country or not. As 111 countries would lead to an unnecessary increase in the size of the features, we only took those 10 countries with the most filled out daily questionnaires. These countries are `['DE', 'US', 'NL', 'CH', 'GB', 'CA', 'RU', 'AT', 'IT', 'NO']`. The second group of features are the four `seasons`, which are also coded as dummy features. The third group contains `age` and `sex`. Note that we did not include the questions `tinnitus loudness` and `tinnitus stress level` as features as they are highly correlated with the target `momentary tinnitus`.
The age is calculated from the date of the completed daily questionnaire and the date of birth. Sex contains two unique values, male and female. The last group of features is a subset of questions of the daily questionnaire. This subset contains information about the momentary mood, arousal, stress level, and concentration. This results in a dataframe with 20 features, 1 binary target, and 74,360 samples from 2,179 users.

RQ1: Is the `momentary tinnitus` of TYT users predictable using the features `country`, `season`, `age`, `sex`, and from the daily EMA questionnaire, `mood`, `arousal`, `stress`, `concentration`, and `worst symptom perception`?

Data preparation. From previous research works, we already knew that the dataset is imbalanced regarding the target. This means that about 75,000 answers are tinnitus = yes, but only 20,000 tinnitus = no. A classifier that has guessed randomly the outcome would get 50 % accuracy on average, a *naive* classifier would simply always predict *Tinnitus=yes* and would get 78.95 % accuracy on average. We therefore draw randomly 54,566 times a sample from the *Tinnitus=no* group, add it to the dataframe, and finally shuffle the samples. This forces each naive classifier to an accuracy down to 50 %. This, in turn, means that any improvement in the accuracy can be attributed to the learning of the classifier.

Machine Learning. The machine learning task at hand is a binary classification task. We wanted to know whether it is possible to predict the occurrence of tinnitus for an individual of the TYT platform. We used a Gradient Boosting Machine[39], which builds an additive model and learns subsequently from prior classification trees. We further divided the data into three sets: Two for cross-validation (the training and the validation sets), and one for the final testing. For cross-validation, we used 70 % for the testing, and 30% for the validation. We stratified on y while splitting in order to retain the 50-50 distribution of the binary target. After a hyper-parameter tuning using gridsearch, we got a **final accuracy of 94.03 %** in the testing set. Details are provided in Fig. 1.



(a) Confusion Matrix for the Gradient Boosting classifier. Although there is a little tendency on false negatives, the overall accuracy of 94.03 % on the test set is significantly better than random guessing.

	Precision	Recall	F1-score	Support
Tinnitus NO	0.908	0.980	0.943	17,709
Tinnitus YES	0.978	0.901	0.938	17,708
Accuracy	0.940	0.940	0.940	0.940
Macro avg	0.943	0.940	0.940	35,417
Weighted avg	0.943	0.940	0.940	35,417

(b) Classification report for the gradient boosting classifier. The tendency to predict `No` rather than `Yes` leads to a larger F1 score for Tinnitus=`No` and a larger recall for Tinnitus=`Yes`

Figure 1. Confusion matrix and classification report for the gradient boosting machine used to predict whether an individual has `momentary tinnitus` or not.

Feature Importance. To find out which of the variables have a high impact on tinnitus prediction, we looked at the feature importance of the Gradient Boosting machine. In order to determine the feature importance more accurately, we have

investigated three methods for this. The first one is called *Gini importance*, the second one is *permutation importance*, while the last one is the *correlation*. These three methods measure the feature importance in different units, which makes it impossible to compare importances between methods. However, to make the results comparable, we have created an importance ranking. The lower (i.e., greener) the ranking number is, the more important the feature for the model to predict the target is. In Table 2, we separated the features into four groups: Countries (with ISO2 country codes), seasons (spring, summer, autumn, winter), demographics (age, sex), and daily questions (mood, arousal, stress, concentration). We further calculated the feature importances for each model (classifier and regressor) separately. To classify the `momentary tinnitus`, demographic features are most important with an average rank of 4.5. The average rank is calculated as the mean of all ranks (Gini, permutation, correlation), for the features belonging to that group. To regress the `tinnitus loudness`, the daily questions are most important with an average rank of 4.16). For both models, `age` is the most important feature (average rank = 2), as it has a high cardinality. Conversely, the countries have a lower importance (average rank = 13.6), since they have only a low cardinality with low variance.

	Did you perceive the tinnitus right now? - Classification						**How loud is the tinnitus right now? - Regression**					
Feature	Gini	Permutation	Correlation	Gini Rank	Perm. Rank	Corr. Rank	Gini	Permutation	Correlation	Gini Rank	Perm. Rank	Corr. Rank
AT	0.4%	0.2%	2.9%	20	20	14	0.4%	0.9%	-3.6%	16	16	16
CA	0.6%	0.9%	4.4%	19	16	11	0.2%	0.5%	-4.7%	19	20	11
CH	1.6%	1.3%	9.4%	14	13	5	0.9%	2.7%	-8.8%	14	14	7
DE	2.4%	2.0%	3.6%	9	9	13	2.0%	8.0%	10.0%	7	7	6
GB	0.9%	0.8%	0.0%	16	17	20	1.1%	3.0%	4.9%	11	12	9
IT	0.6%	0.3%	7.6%	18	19	7	0.2%	0.7%	-1.4%	18	18	20
NL	0.9%	1.0%	0.3%	15	15	17	0.7%	1.9%	-10.3%	15	15	5
NO	0.8%	0.4%	7.5%	17	18	8	0.3%	0.6%	-3.7%	17	19	14
RU	2.2%	1.1%	13.4%	10	14	3	0.2%	0.7%	-1.7%	20	17	19
US	2.1%	2.3%	7.8%	11	7	6	1.0%	3.4%	4.1%	13	11	12
spring	1.9%	1.3%	0.1%	12	12	18	1.1%	3.5%	-4.8%	12	10	10
summer	1.9%	1.7%	1.6%	13	11	16	1.3%	2.8%	-3.1%	10	13	17
autumn	2.5%	1.9%	3.9%	7	10	12	1.3%	4.0%	5.0%	9	9	8
winter	2.5%	2.2%	5.2%	8	8	10	1.6%	4.6%	2.8%	8	8	18
age	24.9%	29.8%	-11.6%	1	1	4	30.6%	93.3%	12.0%	1	1	4
Male	3.8%	4.4%	6.4%	6	6	9	3.3%	15.2%	-4.1%	6	5	13
mood	9.1%	11.4%	-18.4%	4	4	1	7.4%	24.6%	-24.0%	4	4	2
arousal	6.7%	8.3%	0.1%	5	5	19	4.7%	12.5%	12.4%	5	6	3
stress	17.4%	16.5%	17.8%	2	3	2	27.3%	48.8%	38.4%	2	2	1
concentration	16.7%	17.3%	-2.3%	3	2	15	14.4%	29.8%	-3.7%	3	3	15

Table 2. Feature importances of the Gradient Boosting Machines (both classifier and regressor) of univariate features with the two targets `momentary tinnitus` and `tinnitus loudness`. To get a better estimate of the feature importance, three different methods have been used: Gini importance, permutation importance, and correlation. The Gini importances within one column add up to 100 %, the permutation importance indicates the absolute increase of the error rate if that features was left out. Since the percentages cannot be compared between columns, but only within a column, the ranks of the feature importances are also given. The greener a cell is, the more important the feature for the target (`momentary tinnitus` or `tinnitus loudness`) is. The features themselves are grouped in countries, seasons, demographics, and daily questions. As `age` is a feature with high cardinality, it clearly helps the tree-based Gradient Boosting Machines to predict the targets. The high feature importance for the variable age could also be an indication of an overfitting of users who have completed very many assessments.

If we firstly divide the features into their groups (country, season, demographics, daily EMA-questions), we can see that the EMA features (questions 4 (mood), 5 (arousal), 6 (stress), and 7 (concentration)) and the demographic features (sex, age) seem to be the most important feature groups on average. The third most important feature group is the season, followed by the countries. `Age` is a very important feature for the Gradient Boosting Machine for two reasons. First, it has a high cardinality (many different values) and second, it has a moderate correlation with current tinnitus. The permutation importance of 29.7 % suggests that the accuracy becomes 29.7 % percentage points worse when the `age` is replaced by a random variable. For example, almost all Russian users have consistently answered the question about current tinnitus in the affirmative. Within the countries feature, Russia therefore has a high correlation with current tinnitus. However, because there are relatively few users compared to all users, the Gini importance for RU only shows a value of 2.19 %.

RQ2: Is the reported loudness of TYT users predictable using the same features like in RQ1?

In the second research question, we want to estimate the `tinnitus loudness` based on the features, which are listed in Table 1. This machine learning task is not a classification, but a regression. Therefore, we tried to optimize the Gradient

Boosting regressor for absolute deviation from the estimated loudness to the true loudness. We refer to this measure as `abs_mean_error`. In contrast to `momentary tinnitus`, there was no skewed distribution with respect to `tinnitus loudness`. This did not, in our estimation, produce a need to generate samples to produce, for example, a Gaussian distribution of the true values. We chose to train the regressor on the mean absolute percent error rate because this measure directly gives a sense of how well or poorly the regressor is performing. In each case, the regressor underestimates the marginal regions (< 0.2 and > 0.7) of the reported loudness and slightly overestimates the middle regions. On average, it is off by 8 percentage points. Thus, if a user reports a loudness of 70 %, the regressor estimates a loudness of 62 - 78 % on average. A density distribution of the reported loudness and the estimated loudness is given in Figure 2.

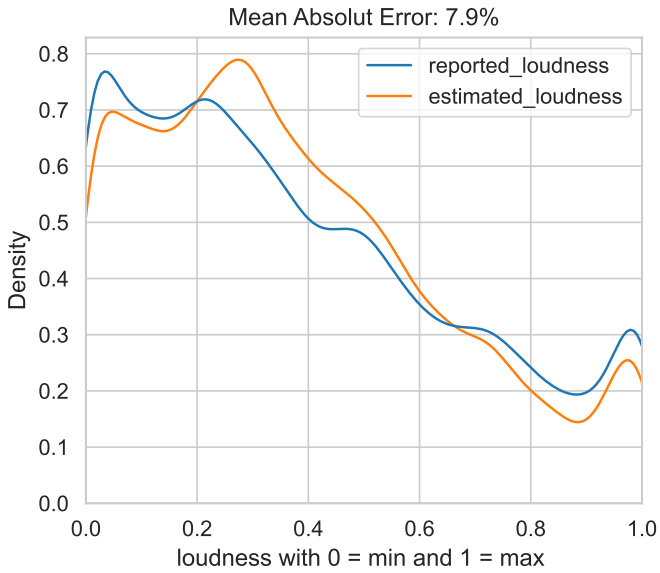


Figure 2. Density curves for the reported loudness and the estimated loudness for all assessments of the test set. Users in the marginal areas tend to be underestimated by the regressor (loudness from 0.0 to 0.2 and 0.7 to 1.0). In the middle ranges (loudness from 0.2 to 0.7), they tend to be overestimated. Nevertheless, an overall performance with a mean absolute error of 7.9%-points is obtained.

RQ3: Are we able to reveal country- and season-specific differences for the reported `momentary tinnitus` based on the daily questionnaire of TYT users?

To answer this question, there are 97,742 responses from 3,691 users from a total of 111 countries for the period from April 2014 to February 2021. For the further analysis, we restricted ourselves to the countries represented by more than 30 users with more than 300 questionnaires in total. For this subset, with 15 countries, 3,163 users remain with a total of 88,049 filled out daily questionnaires. Most responses are from Germany with 51,804 completed questionnaires, generated by 1,410 users, whereas the fewest completed questionnaires come from the Federative Republic of Brazil, with 334 completed questionnaires, generated by 50 users. The mean number of filled out questionnaires per country is 5870 (std = 13,058). The mean number of users is 210 (std = 357). For the question of interest *Did you perceive the tinnitus right now?* (`question1`), mean for 'Yes' is 78.97 % (std = 12.21 %), an interquartile range of 15.73 %, with a maximum value of 95.58 % from Italy, and a minimum value of 48.66 % from Norway, was found.

RQ3_1: Are there country-specific differences for the `momentary tinnitus`? A chi-square test of independence showed that there are significant differences between the countries, $\chi^2(14, N = 85933) = 2441.44, p < .001$. 105 post-hoc χ^2 tests were performed to compare pairwise differences. Using corrected p-values, 91 pairs of countries were rejected (p = .05). 14 pairs could not be rejected at p = .05, i.e., the pair Germany-Great Britain, and Germany-Sweden. This indicates that these countries have a similar pattern in `momentary tinnitus` occurrence. A detailed overview of the answers of `question1` (*Did you perceive the tinnitus right now?*) is given in Table 3.

RQ3_2: Are there season-specific differences for the `momentary tinnitus`? To answer this question, we again analysed only countries represented by more than 30 users with more than 300 completed questionnaires *per season*. This filter setting holds True for Switzerland, Germany, the United States, Great Britain, and the Netherlands. The largest sample is again for

Country_Name	No	Yes	n_questionnaires	n_users
Australia	14.5%	85.5%	666	77
Austria	29.6%	70.4%	1321	68
Belgium	28.6%	71.4%	972	44
Brazil	8.7%	91.3%	344	50
Canada	13.9%	86.1%	2341	126
France	16.6%	83.4%	467	72
Germany	21.0%	79.0%	51804	1410
Italy	4.4%	95.6%	1220	81
Netherlands	33.1%	66.9%	7268	180
Norway	51.3%	48.7%	1178	42
Spain	9.3%	90.7%	517	82
Sweden	18.2%	81.8%	362	38
Switzerland	32.8%	67.2%	5139	122
United Kingdom	20.5%	79.5%	3713	210
United States of America	12.8%	87.2%	10737	561

Table 3. `Momentary tinnitus` by country for individuals of the TYT platform grouped by country. When filling out a questionnaire, most users state that they perceive the tinnitus at that moment. The chance for this is 78 %, with a standard deviation of 12 percent.

Germany, with 51,534 completed questionnaires, the smallest sample is for the UK, with 3,684 completed questionnaires. If we do not group by country, it can be seen that the greatest probability for `momentary tinnitus` is in summer with 83.4% (std = 8.6%). In contrast, the lowest probability for `momentary tinnitus` is in winter, with 71.0 % (11.8 %). The interquartile range is 14.5 % for winter, and 11.8 % for summer. If we group by country, the highest probability for `momentary tinnitus` is in summer in Great Britain (95.7 %), the lowest in winter in Switzerland (60.7 %). The ratios of yes-no-responses are shown in Fig. 3. Considering not only these five countries, but all 111 countries in the present data set without setting a questionnaires or user threshold, the probability of `momentary tinnitus` perception is 80.6 % in summer, 80.1 % in fall, 78.6 % in spring, and 75.1 % in winter. A χ^2 test of independence showed that there was a significant association between season and `momentary tinnitus`, $\chi^2(3, N = 95446) = 216.19, p < .001$. Overall user reporting for tinnitus is thus most likely in summer.

		Age F(4, 2267) = 5.17, p < 0.001								Handesness $X^2(8, N=2319) = 6.64$, p=0.58			Family History $X^2(4, N=2314) = 4.33$, p=0.36	
Country	Sex	Count	Mean	Std	Min	25%	50%	75%	Max	Left	Both Sides	Right	No	Yes
CH	Female	32	48.38	13.84	31	37	47	62	74	0.0%	9.1%	90.9%	69.7%	30.3%
	Male	78	49.94	13.95	21	39	50	59	78	12.5%	17.5%	70.0%	71.3%	28.8%
DE	Female	414	44.36	13.80	8	33	46	55	79	10.5%	13.1%	76.4%	74.3%	25.7%
	Male	851	49.15	13.83	10	39	50	58	87	10.6%	13.1%	76.3%	79.3%	20.7%
GB	Female	91	41.81	12.33	17	32	42	51	70	8.8%	15.4%	75.8%	74.7%	25.3%
	Male	106	46.12	13.13	13	37	46	57	71	13.2%	7.5%	79.2%	78.5%	21.5%
NL	Female	25	50.76	12.07	29	43	47	61	73	5.9%	14.7%	79.4%	73.5%	26.5%
	Male	95	45.79	14.12	18	34	50	57	73	14.0%	8.1%	77.9%	73.5%	26.5%
US	Female	242	47.71	13.19	12	38	49	57	84	14.9%	8.9%	76.2%	69.6%	30.4%
	Male	284	51.58	12.68	16	43	54	60	81	11.5%	12.8%	75.7%	78.9%	21.1%
all*	Female	1102	44.46	13.60	8	33	45	55	84	11.2%	13.4%	75.3%	72.7%	27.3%
	Male	2231	47.15	13.95	1	37	48	57	114	12.9%	15.7%	71.4%	78.2%	21.8%

Table 4. Statistical comparison of the five countries CH, DE, GB, NL, and US with all users. Additionally, the data is grouped by gender. For the χ^2 tests, the N differs from the Count column, as some data is missing. The χ^2 for *handedness* and *family history* is not significant. For the comparison of the age distributions, the post-hoc Tukey test shows significant mean differences for Germany with the United States ($p < 0.05$), and Great Britain with the United States ($p < 0.01$). The table supports the comparability of the five countries that are mainly discussed in RQ3. *The five countries CH, DE, GB, NL, and US are included in `all` countries.

In a slightly different approach, we considered months instead of seasons. Therefore, we increased the granularity of the x-axis. In addition, we examined the respective average temperature per month in relation to tinnitus occurrence for the countries considered (Switzerland, Germany, U.S., Great Britain, and the Netherlands). When multiple temperature data points from different cities were available for a country, they were aggregated with the average.

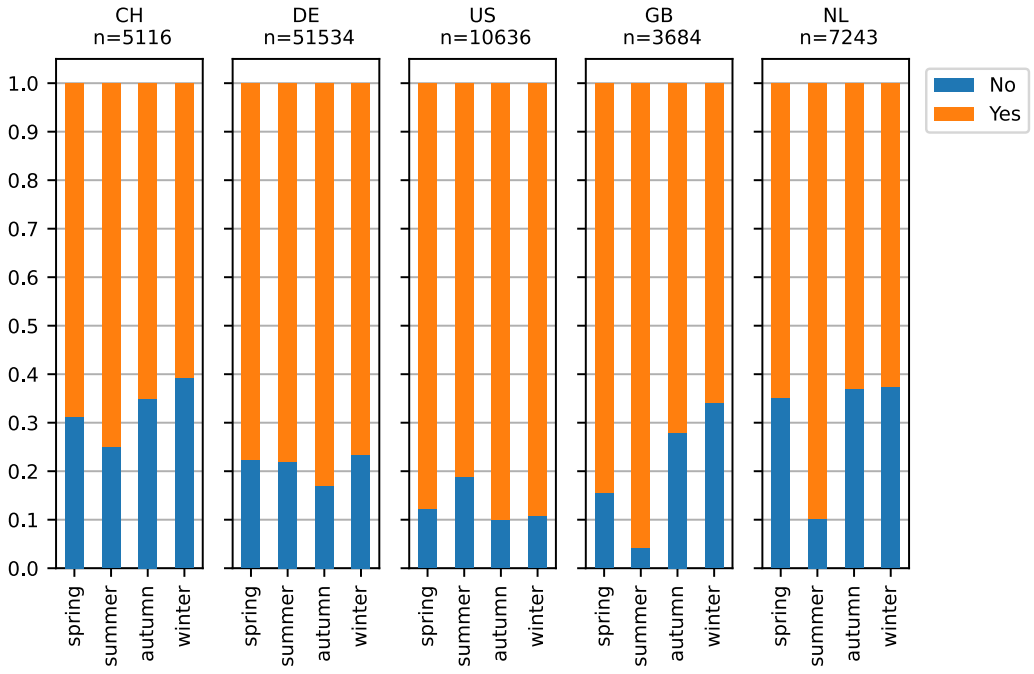


Figure 3. Distribution of the `momentary tinnitus` (*Did you perceive the tinnitus right now?*) by country and season for Switzerland (CH), Germany (DE), the United States of America (US), the United Kingdom of Great Britain & Northern Ireland (GB), and the Netherlands. *n* denotes the number of filled out daily questionnaires per country for all seasons.

A high positive correlation can be obtained for the Netherlands ($r(10) = .83$, $p < .001$), for Great Britain ($r(10 = .86$, $p < .001$), and for Switzerland ($r(10) = .72$, $p = .009$). On the contrary, the U.S. shows a non-significant medium negative correlation ($r(10) = -.41$, $p = .18$). For Germany, however, the correlation between temperature and tinnitus occurrence can be considered uncorrelated ($r(10) = -.09$, $p = .78$). The cyclical temperature pattern associated with tinnitus over the year for the various countries is shown in Fig. 5. There was a statistically significant difference between the countries as determined by one-way ANOVA ($F(4, 55)= 6.69$, $p < .001$). A post-hoc Tukey test indicates that the annual course of `momentary tinnitus` is different between the country pairs Netherlands-U.S. ($p < .01$) and Switzerland-U.S. ($p < .01$).

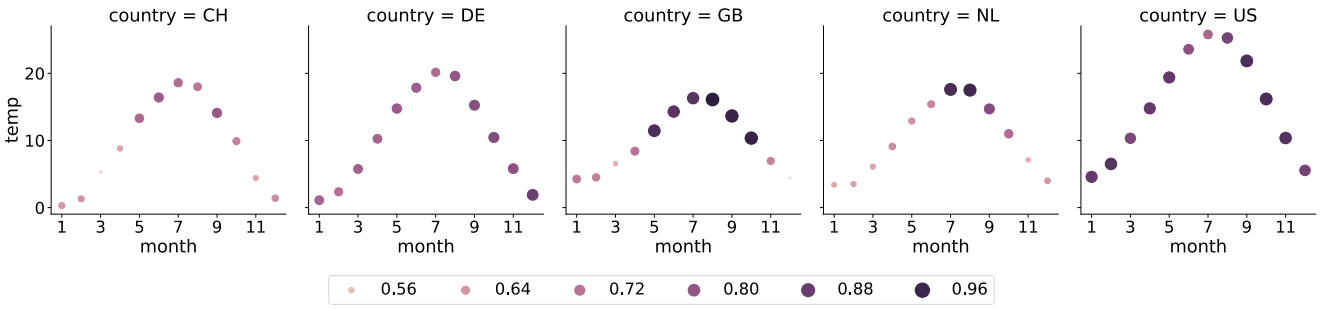


Figure 4. Cyclical temperature pattern associated with tinnitus for Switzerland (CH), Germany (DE), the United States of America (US), the United Kingdom of Great Britain & Northern Ireland (GB), and the Netherlands. The x-axis shows the month, the y-axis the temperature in degrees Celsius. The larger the circle is, the higher the average probability for a `momentary tinnitus` for this country in this month is. The size and color of the cycles indicate the chance of `momentary tinnitus`. The bigger the cycle, the higher the chance.

RQ3_3: In the light of a combination of country- and season-specific differences, the question arose, whether the `momentary tinnitus` varies within the year and across countries. In contrast to the previous section, we have ignored temperature in this question. Instead, we examined the following: For each of the countries considered, and for each individual

month of the year, we calculated the probability of tinnitus by dividing the number of yes responses by the sum of responses. In the following step, we examined the probability of tinnitus over the course of the year. To increase comparability, we additionally calculated the average of the tinnitus probability for all available data on a monthly basis.
Since most of the data comes from Germany, this country has a correspondingly large influence on the average values. Accordingly, the curve for Germany is very similar to the curve of all data (statistic = .17, p = 1.00). On the contrary, the Netherlands, the U.S., and Switzerland reveal a different distribution of the tinnitus with p-values < 0.01. For Great Britain, the distribution can be considered to be slightly different as p-value is .10. An overview of the distributions compared with with the average is given in Fig. 5. A summarizing statistical overview, in turn, is given in Table 5.

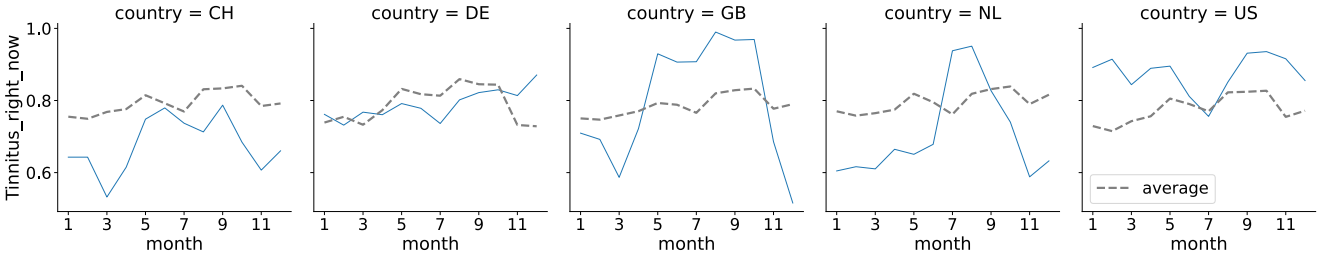


Figure 5. Course of occurrence of tinnitus over the year for Switzerland (CH), Germany (DE), the United States of America (US), the United Kingdom of Great Britain & Northern Ireland (GB), and the Netherlands. The x-axis shows the month, the y-axis the probability for tinnitus occurrence. The dashed grey lines show the average of tinnitus occurrence for all data *except* the country plotted on this axis. The graph indicates that people of different nations perceive tinnitus differently throughout the year.

country	count	mean	std	min	25%	50%	75%	max
CH	12.00	0.68	0.08	0.53	0.64	0.67	0.74	0.79
DE	12.00	0.79	0.04	0.73	0.76	0.78	0.82	0.87
GB	12.00	0.80	0.16	0.52	0.69	0.81	0.94	0.99
NL	12.00	0.71	0.13	0.59	0.61	0.66	0.76	0.95
US	12.00	0.87	0.05	0.76	0.85	0.89	0.91	0.94

Table 5. Statistics for the occurrence of tinnitus throughout the year grouped by country. For this data set, `momentary tinnitus` occurred least in Switzerland in March (53 %), and most in the UK in August (98 %).

The highest probability for tinnitus is in America with an average chance of 87 %, the lowest probability in Switzerland with 68 %. The largest variance occurs in Great Britain, with 16 % standard deviation, the smallest in Germany, with 4 %. For this data set, tinnitus occurred least in Switzerland in March (53 %), and most in the UK in August (98 %).

RQ3_4: The question arose, whether country- and season-specific differences of the reported worst symptom can be identified. To answer this research question, we again focused on the five countries `[CH, DE, GB, NL, US]`. When registering on the TYT platform, the question about the worst tinnitus symptom is asked once. For each country and season, we calculated the relative number of answers within a country to compare which symptom is more likely in which season. Each column adds up to 100 %. The 1,310 users from Germany had the lowest standard deviation (.94 std). The Netherlands with 175 users had the largest standard deviation (2.01 std). *I find it harder to relax* is the most likely symptom in the Netherlands in fall, with 8.57 %, and, at the same time, with a global maximum. *Feeling depressed* ranks second for the UK and the Netherlands. For the U.S., the two worst symptoms are *difficulty following a movie or conversation* and *concentration problems*. For the U.S., however, there is little variation between seasons within these two worst symptoms. *None of these symptoms* ranks second for Switzerland. *Irritability with friends and family* is the least indicated worst symptom for all countries.

In a similar approach, we disregarded countries and investigated the evolution of the worst tinnitus symptom between seasons. Thus, we examined whether there are different worst symptoms per season. *Because of the tinnitus I am more irritable with my family, friends and colleagues* is the most unlikely symptom (mean = 5.9 %, std = 1.0 %. The most likely symptom constitutes *I find it harder to relax because of the tinnitus* (mean = 17.7 %, std = 1.9 %). Details are given in Fig. 6. Difficulties in relaxing is the worst symptom across all seasons. The data further indicates that feelings of depression are stronger in the months of autumn and winter. Difficulties in following conversations are more pronounced in summer. Irritability with

worst_symptom	season	CH (n=114)	DE (n=1310)	GB (n=201)	NL (n=175)	US (n=537)
Because of the tinnitus I am more irritable with my family, friends and colleagues.	spring	0.00%	1.91%	0.50%	1.14%	0.93%
	summer	0.00%	1.37%	1.00%	1.14%	1.86%
	autumn	1.75%	1.68%	0.50%	2.29%	2.23%
	winter	0.88%	1.53%	1.00%	0.57%	0.93%
Because of the tinnitus I am more sensitive to environmental noises.	spring	4.39%	2.67%	1.99%	1.14%	1.49%
	summer	0.88%	1.83%	1.00%	1.71%	2.23%
	autumn	4.39%	2.90%	0.50%	4.00%	2.61%
	winter	2.63%	2.14%	1.00%	0.00%	1.68%
Because of the tinnitus it is difficult to concentrate.	spring	0.88%	3.44%	2.49%	2.86%	4.66%
	summer	2.63%	2.90%	1.99%	1.14%	2.79%
	autumn	0.88%	3.66%	1.49%	6.29%	5.21%
	winter	1.75%	2.60%	1.00%	3.43%	2.79%
Because of the tinnitus it is difficult to follow a conversation, a piece of music or a film.	spring	2.63%	3.36%	3.48%	1.14%	4.28%
	summer	2.63%	2.98%	5.97%	3.43%	4.66%
	autumn	3.51%	4.12%	2.49%	3.43%	3.17%
	winter	2.63%	3.59%	2.49%	1.71%	3.91%
Because of the tinnitus it is hard for me to get to sleep.	spring	4.39%	2.60%	2.99%	1.14%	3.54%
	summer	1.75%	1.98%	2.99%	0.57%	2.98%
	autumn	0.88%	3.36%	4.98%	5.14%	3.17%
	winter	3.51%	2.67%	5.47%	1.71%	4.10%
I am feeling depressed because of the tinnitus.	spring	3.51%	1.91%	2.99%	3.43%	0.93%
	summer	0.88%	2.14%	4.48%	2.86%	2.05%
	autumn	4.39%	2.14%	4.48%	5.14%	3.91%
	winter	1.75%	1.60%	6.47%	2.86%	2.79%
I don't have any of these symptoms.	spring	6.14%	2.67%	1.00%	0.00%	1.68%
	summer	1.75%	2.37%	1.00%	1.71%	1.68%
	autumn	4.39%	3.05%	1.00%	2.29%	2.42%
	winter	7.89%	2.37%	1.99%	2.29%	2.42%
I find it harder to relax because of the tinnitus.	spring	4.39%	5.19%	6.97%	5.71%	4.47%
	summer	7.89%	3.44%	2.49%	4.57%	3.54%
	autumn	3.51%	5.57%	4.48%	8.57%	3.91%
	winter	3.51%	3.28%	7.96%	2.86%	2.23%
I have strong worries because of the tinnitus.	spring	3.51%	2.21%	2.99%	0.00%	2.79%
	summer	0.88%	2.60%	1.49%	4.57%	1.49%
	autumn	1.75%	3.59%	3.48%	6.29%	1.68%
	winter	0.88%	2.60%	1.49%	2.86%	2.79%

Table 6. Distribution of the worst symptom for each country and season. We only considered countries with more than 300 questionnaires from more than 30 users. Each column adds up to 100 %. *n* denotes the number of users from this country.

colleagues or family is the least selected symptom. However, a chi-square test of independence showed that there was no significant association between worst symptom and season, $\chi^2(24, N = 3458) = 30.86$, $p = .16$.

Discussion

The present work investigated the differences of `momentary tinnitus` in relation to seasons and countries. Although we found significant differences between seasons and countries, this does not establish causality between the variables. Although our findings potentially provide important insights for further tinnitus research, there are a few limitations that should be discussed. First, there might be a myriad of other reasons why tinnitus is more likely in some countries in summer and in some in winter. Influencing factors could be, for example, air pressure, stress level, or the number of hours of sunshine. Second, user numbers vary widely between countries. This can lead to a selection bias in the evaluation. Consider the filter criterion "at least 30 users per country". If one user was particularly active in filling out the daily questionnaire, and the other 29+x users were not, this might lead to a selection bias. Third, although our research results indicate different seasonal trends for tinnitus for different countries, there may be individuals who perceive tinnitus seasonally quite differently, possibly even completely in the opposite direction. This means that these findings are not applicable to individuals.

For the worst tinnitus symptom per country and season, comparability between countries and seasons may also be biased by the selection due to the low number of users per category. For Switzerland, for example, we would expect 3.17 individuals per symptom per season (i.e., 2.8 % per line), if symptoms and seasons were equally distributed. In this respect, it is surprising for Switzerland, for example, that *relaxation* is more difficult in summer (7.89 %) than in winter (3.51 %). The situation is different with Germany. Here, we have a large number of users of 1,310 and would expect 36.4 individuals per category, if the

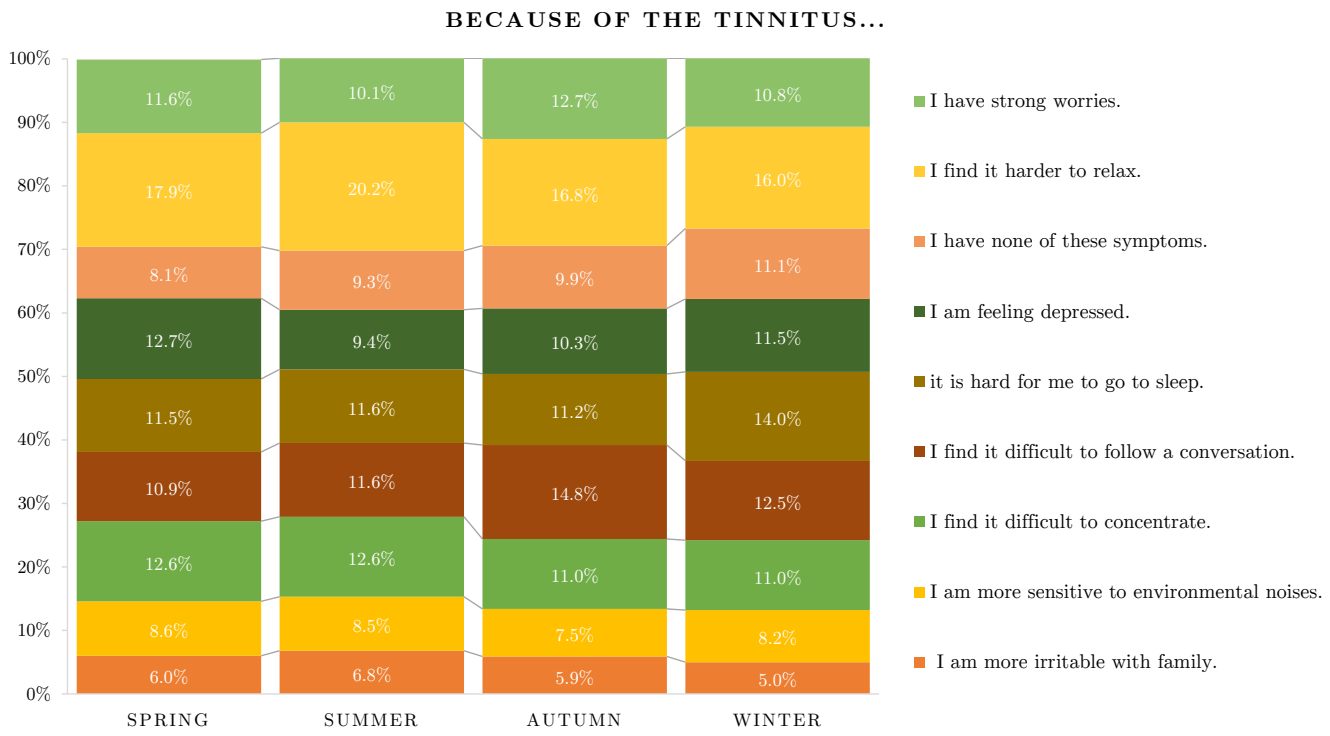


Figure 6. Development of the worst symptom for tinnitus over the seasons. For countries in the southern hemisphere, the seasons have been inverted. Users are asked this question once when completing the baseline questionnaire (n = 3458). *Irritability with friends and family* is the least selected symptom, *difficulty with relaxation* is the most selected. Difficulty following a conversation has a clear high in summer. The values for each season add up to 100 %. A chi-square test of independence showed that there was no significant association between worst symptom and season, $\chi^2(24, N=3458) = 30.86$, p=.16.

symptoms were equally distributed among all seasons. This argument is supported by the fact that the variance in Germany is lower than in Switzerland. Nevertheless, we can observe for Germany that *relaxation* is more difficult for spring and autumn (about 5 %) than for summer or winter (about 3 %).

The accuracy depends on which level we split: Accuracy level vs user level. By stratifying at the **assessment level** (i.e., on the level of filled out questionnaires), one can ensure that the distribution of the target between test and training data remains the same. The specific problem at hand is that several users have filled out different numbers of assessments. There are many users with only one or two assessments, and a few users with several hundred or thousand assessments (so-called power users), as you can see in Fig. 7. These power users are highly likely to be present in the training, validation, and testing data. Any model is therefore predestined to an overfitting on these power users. One can address this problem by excluding users that are in the training set from the test set and vice versa. We then no longer evaluate at the assessment level, but at the **user level**. However, the accuracy in the test set then drops from 94 % to around 50-60 %, depending on different test sets with different power users. That is, the model can hardly predict assessments from users it has never seen before.

There are features that are user-dependent and therefore reduce the number of learnable parameters in the model when splitting the data at user level. These include, for example, country, gender, age, and season. If by chance there are only German users in the training data, but English users in the test data, then the feature country has no more variance and therefore no prediction power for the model. As another example, if a male user who is 43 years old reports the `momentary tinnitus` as "Yes", several hundred times, then the model learns that 43 year old males always have tinnitus. However, this would have nothing to do with the dynamic assessments and therefore contradicts the idea of Ecological Momentary Assessments. This would partially explain the drop in accuracy between the training and test sets. We therefore took a subset of the features that we know retain their variance, even when split at the user level. These features are `mood, arousal, stress and concentration`. If we now split at the assessment level, i.e., allow the same users in the training and test data, we get an accuracy of 84 % in the test set, which is significantly better than guessing. If we now additionally split on user level, the accuracy drops again to 50-60 %, which suggests an overfitting of the training users. Thus, the model cannot predict

assessments of users that it has not yet seen, or to put it in another way: The completion behavior of the individual user varies so much between the users that one can hardly conclude from user A to user B.

The bias in the selection of users remains: A user who has completed many assessments is represented in both the train and test data, which raises doubts about the generalizability of the model, since one may have trained a user-specific model. On the other hand, if one tries to stratify for users, the distribution of the target, and demographic data, no more data remain and one would have to collect a large amount of more data, which is expensive and time consuming. Any stratification technique eventually creates a bias. We decided for the user bias to be able to stratify correctly for the target. This also allowed us to use more data to train our models. The generalizability of the model to users from a different population is not known. However, it is known that the model can make predictions at the assessment level for users who come from a known population. This is shown by the high accuracy of the test set at the assessment level. In current investigations, we evaluate these differences more in-depth.

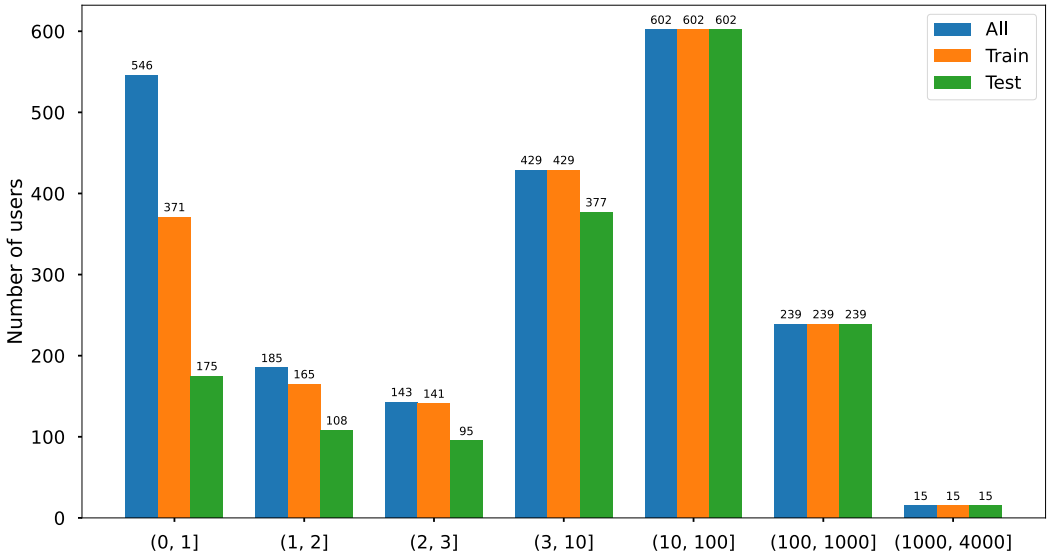


Figure 7. Number of users by range of filled out questionnaires. If we take only users that filled out one single assessment, we also automatically split on a user level. That is, the model predicts only on users it has never seen before. However, if we include users that have filled out the questionnaire more than 10 times, the likelihood that is users is represented in both the train and test set is very high.

Feature Importance High cardinality features such as `age` and the daily questions are assigned with a higher importance as these features can be easily split up into multiple, potentially pure subsets. For binary features, the tree classifier can only split up the data once. However, for features with high cardinality, the tree can potentially split up the data `n_unique - 1` times. Feature importance does not establish causality between input variables and target. It is rather an estimator of which variable has the greatest predictive power for the Gradient Boosting machine. Any other classifier, such as a neural network, would potentially produce a different ranking for feature importance. Among the percentages, the 93.3 % permutation importance for `age` in the regressor model is prominent. The 93.3 % induces that the model loses almost all its predictive power without the `age` feature. However, since the model was trained and evaluated with the *mean absolute error*, this percentage value cannot be easily transferred to the mean absolute error, but is only an indicator for the importance for the model.

Worst Season for Tinnitus We define one season as worse than another if the probability of the `momentary tinnitus` is higher on average. This question cannot be answered unambiguously and conclusively. Related work on tinnitus and seasonality does suggest winter as the worst season[11,13,14]. However, 41.8 % of individuals (n = 100) report perceiving summer as the second worst season, which argues against the theory of seasonal affective disorders[40]. In the study, which aggregated tinnitus search requests from online platforms by season and country, winter was also highlighted as a more frequent season. In the study, which aggregated tinnitus search requests from online platforms by season and country, winter was also highlighted as a more frequent season[11]. However, the results are different, even for countries with similar longitudes. For example, this is the case for Sweden and the United Kingdom. The noise in the results could be due to confounders, or the mentioned selection bias.

Outlook In future work, we are heading into two research directions. At first, we plan to compare the results of TYT to other data sources that have similar characteristics. Second, a more in-depth inspection of the user- and assessment perspective of TYT in particular will be considered.

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Acknowledgements

This work was partly funded by the ESIT (European School for Interdisciplinary Tinnitus Research[41]) project, which is financed by European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement number 722046 and the UNITI (Unification of Treatments and Interventions for Tinnitus Patients) project financed by the European Union's Horizon 2020 Research and Innovation Programme, Grant Agreement Number 848261.

Author contributions statement

J.A. primarily wrote this paper, created the figures, tables and plots, and trained the machine learning algorithms. W.S., B.L., T.P. and R.P. carefully read and revised the paper. Everybody contributed to the methodology. R.P. supervised the paper.

Supplementary Information

The Python code to replicate the Machine Learning classifiers, figures and tables is available on github.com/joa24jm/tinnitus-country.

Additional Information

The authors declare no competing interests.