727521 – EVOTION

DELIVERABLE No: D3.1

Public Health Policy Decision Models (PHPDM) v1

Authors: Panagiotis Katrakazas, Thelma Androutsou (ICCS), Andrew Smith (CITY), Louisa Murdin, Nina Koloutsou (GST), Josip Milas, Dario Brdarić (IPH), Adam Dudarewicz, Małgorzata Pawlaczyk-Łuszczyńska, Mariola Śliwińska-Kowalska (NIOM), Niels Henrik Pontoppidan (OTC), Lyubov Trenkova, Gergana Kaloyanova, Nadezhda Tsokova (PRA), Doris-Eva Bamiou, Giorgos Dritsakis (UCL), Athanasios Bibas, Dimitris Kikidis (UoA)

Dissemination level	
PU	Public

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727521

Project acronym and GA no	EVOTION- 727521
Project full Title	EVidenced based management of hearing impairments: Public health pOlicy making based on fusing big data analytics and simulaTION.
Project Type	RIA
Start date – end date	01.11.16 – 31.10.19
Website	www.h2020evotion.eu
Deliverable type	DEM – ***NB: Report contains external links for verification of demonstrators, see section 6***
Delivery date	M12 (31 OCT 2017)
Authors/contributors:	Panagiotis Katrakazas, Thelma Androutsou (ICCS), Andrew Smith (CITY), Josip Milas, Dario Brdarić (IPH), Louisa Murdin, Nina Koloutsou (GST), Adam Dudarewicz, Małgorzata Pawlaczyk-Łuszczyńska, Mariola Śliwińska-Kowalska (NIOM), Niels Henrik Pontoppidan (OTC), Lyubov Trenkova, Gergana Kaloyanova, Nadezhda Tsokova (PRA), Doris-Eva Bamiou, Giorgos Dritsakis (UCL), Athanasios Bibas, Dimitris Kikidis (UoA) Reviewed by Ariane Laplante-Lévesque (OTC), Dimitrios Koutsouris (ICCS), Petros Toumpaniaris (ICCS)
Contact:	Panagiotis Katrakazas (pkatrakazas@biomed.ntua.gr)
To be cited as:	Katrakazas, P et al (2017), Public Health Policy Decision Models (PHPDM) v1, Deliverable D3.1 to the EVOTION-727521 Project funded by the European Union, ICCS, Greece
Subject and keywords	This deliverable includes the documentation of the initial PHPDM models based on the analysis of static clinical data. EVOTION Public Health Policy Decision Models, Hearing Care, Hearing loss, Big Data
Disclaimer:	This document's contents are not intended to replace consultation of any applicable legal sources or the necessary advice of a legal expert, where appropriate. All information in this document is provided "as is" and no guarantee or warranty is given that the information is fit for any particular purpose. The user, therefore, uses the information at its sole risk and liability. For the avoidance of all doubts, the European Commission has no liability in respect of this document, which is merely representing the authors' view.

Contents

List of Figures

List of Tables

List of Abbreviations

AT	AUDITORY TRAINING
BDA	BIG-DATA ANALYTICS
DALY	DISABILITY-ADJUSTED LIFE-YEAR
DOA	DESCRIPTION OF ACTION
ED	EVOTION DATA
ENT	EAR NOSE THROAT EXPERTS
GHABP	GLASGOW HEARIND AID BENEFIT PROFILE
HA	HEARING AID(S)
HADS	HOSPITAL ANXIETY AND DISORDER SCALE
HL	HEARING LOSS
HUI-3	HEALTH UTILITIES INDEX MARK 3
IOI-HA	INTERNATIONAL OUTCOME INVENTORY FOR HEARING AIDS
MAR	MISSING AT RANDOM
MCAR	MISSING COMPLETELY AT RANDOM
MNAR	MISSING NOT AT RANDOM
MOCA	MONTREAL COGNITIVE ASSESSMENT
PERI	PROBLEM, ETIOLOGY, RECOMMENDATIONS AND IMPLEMENTATION
PHP	PUBLIC HEALTH POLICY
PHPDM(s)	PUBLIC HEALTH POLICY DECISION MODEL(S)
PTA	PURE TONE AUDIOMETRY
SIN	SPEECH IN NOISE
SPL	SOUND PRESSURE LEVEL(S)
TTS	TEMPORARY THRESHOLD SHIFT

Executive Summary

This document presents the first version of the public health policy decision models (PHDPMs) developed in the EVOTION ecosystem. These models were the joint effort between public health policy (PHP) makers, clinical experts, and technical partners in the EVOTION consortium. The models combine experience and knowledge from the three aforementioned fields. To the best of our knowledge, this is the first attempt showing that big data can enhance existing PHP modelling procedures with better-monitored evidence-based actions. Moreover, the deliverable is an attempt to provide PHP makers with the easy access to heterogeneous big data what can assist then tack major health issues, like hearing loss, through holistic prevention and management of public policies.

The information found herein includes:

- A generic description of the PHPDMs according to the EVOTION concept;
- A description of each of the four (4) PHPDMs to be developed;
- One indicative use case that serves as demonstrator;
- External links for assessing the verification means of the demonstrator.

1. Introduction

1.1 Overview

As shown by a recent study, the effective implementation of research informed PHP requires actions to be taken not only by decision makers but from researchers as well. The transfer of current knowledge found in big data collections, along with the usefulness of models, underpin the procedure of PHP decision making (Orton et al., 2011).

Work Package 3 (WP3) in EVOTION focuses on the development of PHPDMs. As highlighted in the Description of Work, the objective of this WP is twofold:

- To identify factors affecting the effectiveness of hearing loss (HL) treatments for different HL patients (with respect to their type of HL and other characteristics including possible co-morbidities of HL patients) in different contexts based on analysis of the EVOTION data.
- To develop PHPDM incorporating simulation models to enable the exploration of the effects of the decisions that they generate.

The work under this work package is divided into four (4) tasks, each focusing on the different types of predictive and PHPDM models. For these purposes, a generic methodology needs to be designed, for it to be incorporated into the Big-Data-Analytics (BDA) environment of the EVOTION platform. As previously described in D2.2 EVOTION Architecture and Detailed Design (Ye et al., 2017), the PHPDM Transformation tool will take the PHPDMs and translate them into a form executable by the BDA. To implement such a methodology, a link between BDA stages (a step-by-step methodology needed to organize the activities and tasks involved with acquiring, processing, analyzing and repurposing big data) and PHPDM needs to be established to successfully convert policy-driven models into analytic ones, able to undertake processing and statistical analysis of health data.

1.2 Purpose and scope of deliverable

The purpose of Deliverable 3.1 is to provide a foundational framework for the development of the PHPDMs in EVOTION. The thematic axis of the current deliverable is to deal with the first two (2) phases of the BDA-PHPDM relationship namely, (i) PHPDM hypotheses articulation and (ii) Data pre-processing, and demonstrate how application of data analytic tasks performed on static data leads to a dynamic outcome, affecting PHP formulation.

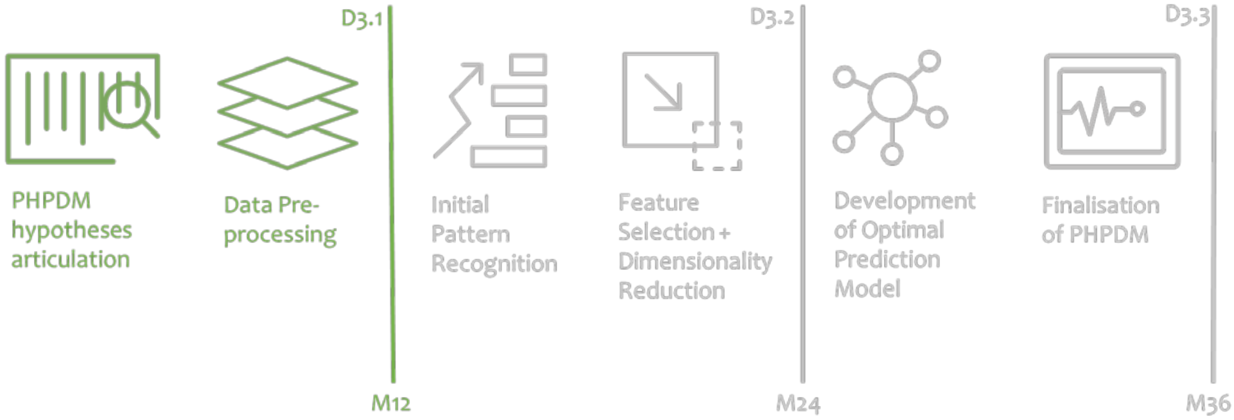

Figure 1 Timeline for WP3 Deliverables (current progress indicated with green colour)

Subsequent phases will consist of (iii) initial pattern recognition, (iv) feature selection and dimensionality reduction, (v) development of the optimal prediction model and (vi) finalization of the PHPDM. These will be explored over the next two deliverables of WP3 (D3.2 and D3.3). Figure 1 shows a visual representation of the progress so far, as well as the next actions to be taken over the remaining duration of the project.

1.2.1 PHPDM hypotheses articulation

In this phase, the basic goals, decision criteria and evidence for the different PHPDM of interest will be identified and defined. These elements will provide the basis for searching into the EVOTION dataspace, an abstraction term referring to the entirety of the EVOTION data sets. These will indicate the basic variables needed for making decisions and hypotheses. They will also identify the factors that may affect them as well as the forms of analysis that may be used in order to produce the evidence expected by the PHPDM.

1.2.2 Data pre-processing

This phase will be concerned with the transformation of the available data of the basic variables and influencing factors identified in 1.2.1, into formats that will be appropriate for further analysis. This will be done by means of feature transformation algorithms. In addition, this phase will involve:

a. **Detection of outliers that might need to be excluded from the data set prior to further analysis**
An *outlier* is an observation that lies an abnormal distance from other values in a random sample from a population. In a sense, this definition leaves it up to the analyst (or a consensus process) to decide what is considered abnormal. Before abnormal observations can be singled out, it is necessary to characterize normal observations (Seadle, 2016).

Outliers in the EVOTION data collection system should be rare, because otherwise the methodology and hence the entire dataset would be characterized as bad and/or untrustworthy. Two activities are essential for characterizing a dataset: (a) examination of the overall shape of the graphed data for important features, including symmetry and departures from assumptions, and (b) examination of the data for unusual observations that are far removed from the mass of data.

Due to the amount of EVOTION data and the nature of the EVOTION computation platform and cloud-based services, distributed versions of regression and classification trees are to be employed, as well distributed robust regression trees (Guo et al., 2016). Scatter- and box-plots, two graphical techniques for identifying outliers along with an analytic procedure for detecting outliers when the distribution is normal (Grubbs' Test) will also be employed.
Identified cases of outliers that should be kept will undergo transformation (e.g. square root and log transformation techniques) or be applied to non-linear models to fit the data with outliers intact. The aforementioned methods will be described in more detail in D3.2, after reviewing the yet to be filled EVOTION datasets.

b. Handling missing data with methods such as statistical imputation and imputation based on machine learning, in order to address problems of missing values and non-conforming values

Missing values must be considered to successfully and efficiently manage and process an amount of data. If missing values are not handled properly, inaccurate data and therefore conclusions may occur.

There are two main types of missing values: Missing Completely At Random (MCAR) values and Missing At Random (MAR) values. The first category concerns missing values that are randomly distributed across all observations while the second category, which is more common, concerns missing values that are not distributed randomly but within one or more sub-samples. There is also a third categorization of values, Missing Not At Random (MNAR) values, that is not often addressed by missing data methods and concerns values that are neither MCAR nor MAR and the probability of them missing depends on the variable that is missing.

There are many statistical techniques and estimation models that identify the aforementioned type of missing values. Statistical imputation includes several methods to handle situations where missing data are likely to occur. Unlike other traditional methods (e.g. listwise deletion) which discard cases with missing data, imputation replaces missing data with an estimated value based on other available information. When all missing values have been imputed, data can then be analysed using standard techniques (Gelman and Hill, 2007). There are two types of imputation: single imputation and multiple imputation. Single imputation methods involve less computation and can be a useful tool when only a small amount of data is missing. Multiple imputation methods are more flexible and can be used in a wide variety of scenarios, especially when there is a considerable number of missing data and single imputation can lead to misleading analyses (Stef van Buuren, 2012). The primary method of multiple imputation is multiple imputation by chained equations (MICE), which is used when the missing data follow MAR mechanism (Azur et al., 2011). Partial imputation (e.g. expectation-maximization algorithm), regression imputation, mean substitution imputation, hot-deck and cold-deck imputation are some of the most prevalent methods of imputation.

Machine learning includes a variety of algorithms based on imputation and other statistical methods. The correct approach depends on the kind of data and the type of missing values that need to be analyzed.

As far as EVOTION is concerned, the nature of data as well as the outliers and types of missing values need to be clearly identified and recognized from the initial stage of collecting them to the processing/analysis stage. This would give the necessary knowledge to apply the aforementioned techniques in accordance with the EVOTION data.

1.3 Public Health Policy Decision Models: An introduction

1.3.1 Definition of a PHPDM

There is a plethora of definitions of decision models for PHP available. A PHPDM can be defined as a mathematical structure developed to synthesize two or more sources of evidence, used to project out the health outcomes associated with alternative policies (Kuntz et al., 2013). A decision model visualizes the sequences of events that can occur following alternative decisions (or actions/policies) in a logical framework, as well as the health outcomes associated with each possible pathway. Decision models can incorporate the probabilities of the underlying factors in determining the distribution of possible outcomes associated with a particular decision (Kuntz et al., 2013).

Public health decisions are taken at the level of communities, regions, or even entire countries rather than individuals as the unit of intervention (Kemm, 2006). Unlike evidence based medicine, in which randomised controlled trials and systematic reviews are mainly drawn upon, evidence for PHP is much more complex. The policy process involves a series of steps: sophisticated data visualisation for situation analysis, problem delineation, option development, priority setting, optimal implementation, and subsequent evaluation. The evidence required at each step is dramatically different. Thus, public health evidence must answer not only the questions of effectiveness and cost-effectiveness of interventions in different populations; but also, organisation, implementation and feasibility, which are less commonly covered by research evidence (Klein, 2003). The tools for integrating and translating scientific data into policy-relevant outcomes are often classified in the domain of ‘mathematical models’ (Heesterbeek et al., 2015; Lofgren et al., 2014). Quantitative evidence for policymaking can take many forms, ranging from scientific information in peer-reviewed journals, to data from public health surveillance systems on for example prevalence of a health problem, to systematic evaluations of individual programs or policies (Bernhardt et al., 2011; Brownson et al., 2009). Qualitative evidence for policymaking can make use of the narrative form as a powerful means of influencing policy deliberations, setting priorities, and proposing policy solutions by telling persuasive stories that have an emotional hook and intuitive appeal (Lindsey and Yun, 2003).

Evidence-based approach to public health policy making can be approached via the Problem, Etiology, Recommendations and Implementation (PERI) framework which is used for defining, analyzing, and addressing a wide range of public health issues. In the EVOTION case, the PERI framework needs to be adjusted in a way to incorporate BDA tasks that can enhance its core functionality.

> **Short Description of the PERI framework**
> The first step in addressing a health **problem** is to describe its impact. The impact refers to the occurrence of disability and death due to a disease and represents the burden of disease.
> Another important issue refers to the way that the disease is spread out or distributed in a population. Usually, public health professionals investigate factors in order to explore patterns or associations in the frequency of a disease. Thus they can suggest ideas about the **etiology** of a disease. In evidence-based public health, a very specific definition of causation contributory cause is used. The evidence-based public health approach relies on epidemiological research studies to establish a contributory cause.
> It is also critical that any action occurs in public health is grounded in **recommendations** that incorporate evidence. Specifically, recommendations are summaries of the evidence of which interventions work to reduce the health impacts and they suggest whether actions should be taken.
> As a result, it is critical to evaluate whether an intervention or combination of interventions has been successful in reducing the problem. It is also important to examine all the options for **implementation** and measure problem's elimination due to the intervention(s). In order to address a public health problem, it is significant to decide the best combination of approaches. This issue remains an important part of the judgment needed for the practice of public health(Riegelman and Kirkwood, 2014).

The primary goal and content of the EVOTION PHPDMs is to provide different stakeholders with tools for policy formulation that will or could help improve health, socio-economic burden and quality of life of the HL population. These models will address HL related policies that can be effective over sustained periods. EVOTION aims to identify factors associated with positive outcomes that will have essential and long-lasting influence in HL populations. They will also support the design of PHP through the development and implementation of strategies, activities and services addressing the HL population.

1.3.2 Diagrammatic Representation of PHPDM

Since a generic vocabulary has to be applied and to allow a better understanding of the steps of the PHP-making process, a set of building elements describe EVOTION PHPDMs, namely: Goals (G), Objectives (O), Decision Criteria (CR), EVOTION Data (ED), Factors (F), Types of Analysis (TA) and Policy Actions (PA). EVOTION dataspace consists of ED and F.

The aforementioned elements derive from the need to introduce the BDA concept (consisting of the ED as found in D5.2 Data Repository and Collection Components (Basdekis et al., 2017) and TA elements) to an adaptation of the PERI framework process. The remaining elements (G, O, CR, F, PA) supplement the BDA elements to form a comprehensive PHPDM.

A visual representation of a generic PHPDM is shown in Figure 2.

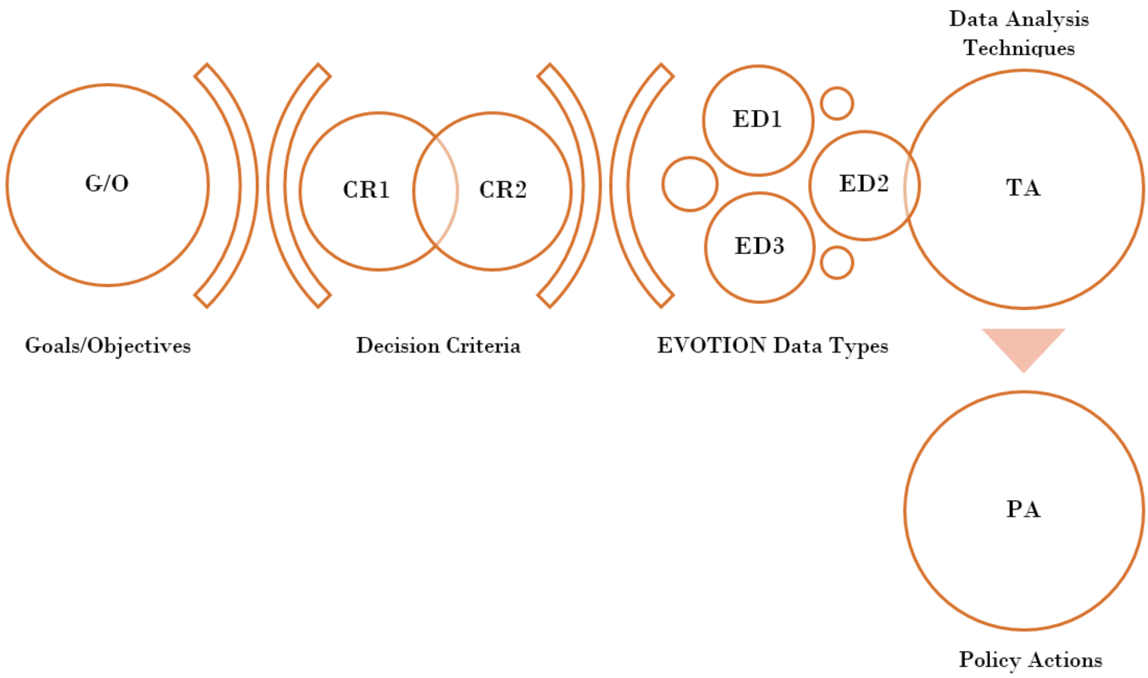

Figure 2 Generic PHPDM Visual Representation

To address the range of PHP-making areas related to HL (

Table 1 shows a redacted format of the relevant table included in the Description of Action), four (4) models have been designed:

- The PHPDM for Prognosis of Effectiveness of HA Usage covers areas [3], [4] and [5],
- The PHPDM for Prognosis and Prevention of Noise Induced Hearing Loss covers areas [1], [2] and [5],
- The PHPDM for Prognosis and Delivery of Effective Auditory Training Rehabilitation Services covers areas [1]-[4].
- The PHPDM for Hearing Loss Management and Overall Well-being of Hearing Impaired Individuals covers areas [2]-[4] and [6]

Table 1 Areas of PHP making in connection to HL treatment, as described in the DoA

	PHP Area	Specific Issues
[1]	Screening/early detection	Improved outcomes related to early detection and management
[2]	Prevention	Prevention of noise-induced hearing loss
		Prevention of cognitive decline
[3]	Treatment rationalization and health system improvement	Hearing aids usage
		Enhancement of HL management choices, including the use of Assistive Listening Devices (ALDs) integrated with hearing aids, and support from tele-audiology
		Follow up care
		HL rehabilitation services (1) Personalising care (2) Quality standards (3) Affordability
		Social care services for HL patients
		Access to non HL related health services
[4]	Comorbidities Monitoring	Treat HL as a long term condition and in an integrated manner based on multi-morbidity long term indicators
[5]	Inclusion	Communication challenges in occupational contexts
		Accessing public services
		Access to public transport
[6]	Safety & Overall well being	Driving
		Walking

1.4 Structure of deliverable

The deliverable is structured in seven (7) sections, which are briefly described below:

- **Section 1** introduces the deliverable and its main goals as well as PHPDMs.
- **Section 2** describes the building elements of the first PHPDM for Prognosis of Effectiveness of HA Usage.
- **Section 3** describes the building elements of the second PHPDM for Prognosis and Prevention of Noise Induced Hearing Loss.
- **Section 4** describes the building elements of the third PHPDM for Prognosis and Delivery of Effective Auditory Training Rehabilitation Services.
- **Section 5** describes the building elements of the fourth PHPDM for Hearing Loss Management and Overall Well-being of Hearing Impaired Individuals.
- **Section 6** shows a selected demonstration scenario, the description of which is based on the second PHPDM.

- **Section 7** concludes the deliverable with a summarized presentation of the aforementioned PHPDMs and the outcomes of introducing BDA to the PHP domain.

2 PHPDM for Prognosis of Effectiveness of HA Usage

2.1 Defining the Decision Model

Currently, the pre-eminent management strategy for HL is the provision of Hearing Aids (HAs). Despite technological advancements, however, the currently available HAs can only partially overcome the deficits associated with HL while the HA user is faced with several challenges (Dillon, 2012). As a consequence, patients need to visit their clinician several times for HA adjustments and sometimes end up not using their HAs, with as a result an untreated HL and subsequent cost implications. New generation HAs support a wide variety of advanced programming settings, including automatic features that do not require user interaction, therefore no user decision is needed. However, literature suggests that older adults do not use these features as they are less able to decide on complex circumstances and alternatives (McCormack and Fortnum, 2013). Thus, the majority (80%) of adults aged 55 to 74 years who would benefit from a HA, do not use them (McCormack and Fortnum, 2013), while nearly 30% of HA users are dissatisfied with their HAs in noisy situations (Kochkin, 2014).

The aim of this model is to define the factors that affect the multi-dimensionality of HA outcome measure (i.e. usage, effectiveness and satisfaction). This measure assesses six (6) dimensions: Intitial Disability, Handicap, Satisfaction, Reported HA use, Residual Disability and Reported benefit. The first two dimensions may be evaluated before interventions, to influence the course of intervention and guide the counselling process. The other four dimensions are used to gauge how an individual is faring after rehabilitation using amplification (Bentler et al., 2016). These dimensions can be measured via the Glasgow Hearing Aid Benefit Profile (GHABP) or the International Outcome Inventory for Hearing Aids (IOI-HA). A better understanding and accurate prediction of the challenges that HA users face in different environments will generate evidence on how to link such information to appropriate, individualised management strategies.

2.2 Basic Goals and Objectives

Goals

G1: provide evidence regarding the current levels of HA outcome measures (usage, effectiveness and satisfaction) to identify potential factors that influence it.

Objectives

O1: identify circumstances under which HAs are underused with the aim to inform the development of strategies aiming towards increase of HA outcomes. Such strategies or policies could include measures with regards to the provision of HAs and continuous support, alerts and other enablers (e.g. auditory training (AT) programmes) to increase HA outcome measures, or the design of targeted interventions to specific populations at high risk.

2.3 Decision Criteria

CR1: Identified factors that influence total refusal to HA and non-shows in follow-up visits, along with overall decrease in the patients' visits between the issued appointment to the next follow-up appointment in six (6) weeks;

CR2: Identified factors that predict a given increase in the six (6) dimensions (Initial disability, handicap, satisfaction, reported HA use, residual disability and reported benefit) of the GHABP-part 2 outcome measures;

Both criteria should follow a validated methodology, applied with best-practises fitting to measure their outcomes and prove the verified efficiency of HAs.

2.4 Evidence supporting the need for PHPDM

Patients with identical HL can show significantly different levels of HA usage and satisfaction. A poor unaided speech discrimination score in noise is a negative predictor for patient-reported HA benefit while user involvement in the rehabilitation process including their personal amplification preferences and retraining are positive predictors for outcome (Borg et al., 2012). However, there is no strong evidence on the effect of self-management support strategies, including system delivery design (Barker et al., 2014).

Outcomes at three different stages in a patient's journey (i.e., prior to the actual HA fitting, during the actual fitting period, and post-fitting) include help seeking, HA uptake, use, and satisfaction. Out of the identified factors that influence these variables, only one (1) factor was found to be positively affecting all of them: self-reported hearing disability (Knudsen et al., 2010). Investigating potential factors that may be used as predictors of low/ineffective usage could help in planning strategies/policies to improve HA users' reported satisfaction. Although systematic reviews (Henshaw and Ferguson, 2013) and randomized clinical trials (Saunders et al., 2016) have indicated poor evidence for the effects of AT, the provision of the EVOTION AT module via the mobile application and its outcome measurements over time, is expected to lead to better acceptance and usage ratings.

Difficulties and minimum usage of HAs in certain locations/environment (e.g., noisy places, open areas with many people), where patients requesting fine tuning appointments on a regular basis while concurrently seeking help to address the problems in certain environments, and poor results of GHAB questionnaires indicate the need for the development of this PHPDM.

2.5 Correlation with EVOTION data

ED1: Satisfaction with HA usage – rating through the EVOTION mobile app and GHABP scores.

Found in **RATING Table** and **PERSONAL_LOG Table**

ED2: HA logging data: periods of HA usage; monaural vs binaural HA use (in binaural HA users) and use of HA controls

Found in **RETRO_HA Table** and **PERSONAL_LOG Table**

2.6 Factors affecting this PHPDM

Environmental data (e.g. user location; noise; outdoor activities) (**F1**), personal data (e.g. education; significant others; age; gender; personal carer; socio economic background; civil status) (**F2**), behavioural data (user daily activities) (**F3**), clinical data (e.g. smoking, diabetes, obesity, family history, ototoxicity medications, duration and type of HL, cause of HL) (**F4**), physiological data (e.g. heart rate) (**F5**), cognitive data (e.g. Montreal Cognitive Assessment -MOCA scores, reaction time, forward and reverse digit recall and mood monitoring via Hospital Anxiety and Disorder Scale-HADS) (**F6**) and occupational data (e.g. employment history and current status) (**F7**)

- **ENVI_DATA Table** (F1, F3)
- **RETRO_HA Table** (F1)
- **Q_DRMED Table** (F1, F4, F7)
- **GHABP_ANSWERS, GHABP_ANSWERS_N, GHABP_RESULT Tables** (F3)
- **PATIENT Table** (F2, F3, F7)
- **MOBILE_AUDIOMERY_RECORD Table** (F3)
- **RATING Table** (F3)
- **BIO_SENSOR Table** (F5)
- **COGNITIVE_TEST_RESULT Table, MOCA_ANSWERS Table, HADS_ANSWERS Table** (F6)

Other types of data that might affect the model, but are outside of EVOTION's platform collecting capabilities, are the following:

- Patient engagement; source of motivation, expectation, attitude
- Clinician-related factors, e.g. competence of the clinician, ability of the clinician to relate to the patient
- Other factors as identified in (Knudsen et al., 2010), e.g. number of major life events, cosmetic appearance of HA, general health attitude.

2.7 Types of Analysis

Identified types of analysis to be employed for this PHPDM include, but are subject to change in case new information occurs:

- **TA1**: Regression
- **TA2**: Statistical correlation analysis
- **TA3**: Principal component factor analysis
- **TA4**: Cost-benefit analysis via 'translating' cost for audiologists' time spent on investigating the factors of low/ineffective HA usage compared to the benefit gained in terms of reduced follow-up appointments, higher patient satisfaction, longer HA usage

2.8 Expected Results

- **PA1**: Provision of HAs better tailored to HA users' characteristics (e.g. "simpler" HAs or more automatic HAs for patient groups with worse scores on cognitive tests, e.g. MOCA)
- **PA2**: Provision of more interactive support, including alerts and other enablers such as information videos and AT programmes, in order to increase the frequency and efficacy of HA usage
- **PA3:** Reduced follow-up appointments for complaints, problems or difficulties with HA use, using the audiologist - monitoring access that provides support and solution to patient concerns or issues and reprogramming/refitting of HAs compared to standards (from literature)
- **PA4:** Update and set-up of standards of HA usage and services

3 PHPDM for Prognosis and Prevention of Noise Induced Hearing Loss

3.1 Defining the Decision Model

In EVOTION project the prognosis and prevention of Noise Induced Hearing Loss (NIHL) will be based on monitoring exposure to loud sounds. Loud sounds can cause two different reductions in hearing sensitivity: Temporary Threshold Shifts (TTS) and Permanent Threshold Shifts (PTS) episodes, named after the effect they have on hearing. TTS means that the threshold returns to the level it had right before the loud sound over a few weeks. However, even if the threshold shift is temporary it may still cause hearing problems, especially for repeated TTS episodes (Kujawa and Liberman, 2009).

These episodes are identified by noise/sound exposure levels high enough to cause temporary or permanent hearing changes.

For this PHPDM, a computational model is applied to the time series of recorded noise levels to predict the temporary threshold shift that it causes, and subsequently alert the individual if the current noise level will affect hearing. In fact, this modelling could lead to two types of policies one for the individual and, if combined with location data, one on a societal level

For predicting TTS, it is possible to use a validated predictive computational model developed by Mills et al. (Mills et al., 1979), Melnick (Melnick, 1991) or later by Czyzewski et al. (Czyzewski et al., 2007) with improvement by Mazur and Voix (Mazur and Voix, 2013) based on the noise exposure over a day (LEQ_{16h}) compared to the critical level (CL)

$$TTS_N = 1.7 \log\left(\frac{\left(10^{\frac{LEQ_{16h}}{10}} + 10^{\frac{CL}{10}}\right)}{10^{\frac{CL}{10}}}\right)$$

The aforementioned model of TTS_N was developed and validated in young subjects with normal hearing. For populations such as HA users with pre-existing sensorineural HL, a specific model has been proposed, that is hereby presented.

It has been shown that TTS produced by a given noise exposure decreases as a function of the degree of pre-existing hearing loss. Thus, the amount of TTS in HA users, could be predicted from the in-ear noise levels and the subject's hearing levels, by means of a mathematical model consisting of the Modified Power Law (MPL) of Humes and Jesteadt (Humes and Jesteadt, 1991) combined with equations for predicting TTS in listeners with normal hearing published by Mills et al. [15].

According to Macrae (Macrae, 1994b) TTS (at a particular frequency produced by noise exposure) in HA users with sensorineural hearing impairment can be predicted form the equation:

$$HL' = 10 \log\left[\left\{\left(10^{\frac{HL}{10}}\right)^P + \left(10^{\frac{TTSn}{10}}\right)^P - 1\right\}^{-\frac{1}{P}}\right]$$

$$TTS_{HL} = HL' - HL$$

where HL' is the shifted threshold in the impaired ear, HL is the initial hearing level of the impaired ear, $TTSn$ is the temporary threshold shift that would be produced by the noise exposure in normal subjects and P is a constant equal to 0.2. The predicted TTS_{HL} in the impaired ear is the difference between the shifted threshold (HL') and the initial HL.

In EVOTION, the TTS prediction models mentioned above, excluding the one developed by Czyzewski et al. (Czyzewski et al., 2007), are used to determine the expected TTS episodes due to specific noise exposure. This will allow for a more successful risk management of TTS, and eventually HA adjustment. Furthermore, environment noise monitoring will also be used as an additional parameter to determine the frequency of occurring PTS episodes (Barrigón Morillas et al., 2016)

3.2 Basic Goals and Objectives

Goals

G1: Deliverance of public policy regarding the prevention of NIHL

G2: Decrease of risk of NIHL in HA user groups exposed to occupational noise

G3: Prevention and decrease of TTS episodes

Objectives

O1: Development of model for PTS/TTS prediction based on cumulative individuals' activities data

O2: Development of trendline of PTS/TTS prediction model based on O1.

3.3 Decision Criteria

CR1: PTS/TTS episodes associated with high external sound levels require intervention for training in the use of HA in a noisy environment.

> Note:
> PTS and TTS are associated with monitoring of sound pressure level outside and inside of ear canal of HA user.
> PTS episode is related to occurrence of sound exposure high enough to cause permanent threshold shift after long-term exposure.
> TTS episode is related to occurrence of sound exposure high enough to cause temporary threshold shift after long-term exposure. It is not associated with actual TTS of HA user.

CR2: The PTS/TTS episodes associated with sound pressure levels at the tympanic membrane require an intervention action to verify the fit and usage of the HA.

If the aforementioned criteria are taken into consideration by PHPM, updated versions of risk factors' and occupational regulations, as well as existing EU standards regarding NIHL, should be applied.

3.4 Evidence supporting the need for this PHPDM

A TTS prediction model will improve self-control of sound exposure of HA users and will allow for early clinical intervention. The external noise might prove to be hazardous to the hearing condition of HA users to a greater extent than that of the general population (Macrae, 1991a, 1991b, 1994a, 1994b, 1995). Assessing the public health impact of NIHL involves consideration of both its prevalence in a particular population, as well as the severity of impact of the condition on affected individuals and populations as a whole (Rossing, 2015).

The international standard ISO 1999 is routinely used to estimate the risk of NIHL. It provides a verified mathematical model for calculating PTS in adult populations following exposure to noise based on four parameters: age, gender, level of noise exposure and duration of noise exposure in years. According to the aforesaid standard the lowest daily (16-hour) noise exposure that might cause NIHL is greater than 77 dBA (ISO 1999:2013, 2013).

Despite recovery of threshold sensitivity, the consequences of primary neuronal loss on auditory processing of suprathreshold sounds are very significant, especially in difficult listening environments (Kujawa and Liberman, 2009). Worldwide, 16% of the disabling HL in adults (over 4 million DALYs - Disability-Adjusted Life Year-) is attributed to occupational noise, ranging from 7% to 21% in the various sub regions. The effects of the exposure to occupational noise are larger for males than females in all subregions and higher in the developing regions (Nelson et al., 2005). Nowadays NIHL is irreversible, necessitating as much effort as possible being put toward prevention. These activities should include identification of high-risk noise exposures, particularly those affecting young people, improvement of noise legislation and effectiveness of use of hearing protectors (Sliwinska-Kowalska and Davis, 2012).

3.5 Correlation with EVOTION data

ED1: Data found in:

- **REAL_TIME_HA Table,**
- **TTSNIHL_TEST_RESULT Table,**
- **MOBILE_AUDIOMERY_RECORD Table.**

will be used for assessment of the SPL at ear drum and PTS/TTS episodes associated with sound pressure levels at the ear drum (as float array)**.**

ED2: Data found in**:**

- **REAL_TIME_HA Table.**

will be used for assessment of external SPL dBA averaged over the entire time of the daily HAs usage (including all periods of HA usage during a day) and PTS/TTS episodes (as float array) associated with the external SPL dBA.

3.6 Factors affecting this PHPDM

Pure Tone Audiometry (PTA) test used for HA fitting HA (**F1**) can be found in the **AUDIOGRAMHEAD Table**, and the daily time HA usage pattern (**F2**) can be found in the **RETRO_HA Table.**

3.7 Types of Analysis

Due to the repetitive nature of TTS episodes, time series analysis will be used to examine responses to similar stimuli in different times. Logistic regression analysis will be also employed due to the binary dependent variables for PTS and TTS episodes (more details can be found in Section 6).

Spearman correlation test will verify the correlation between the indicators of service evaluation and satisfaction with the HAs. The variables which will have p values less than 0.30 will be in the multivariate model (Barbosa et al., 2013).

Therefore, identified types of analysis to be employed for this PHPDM include, but are subject to change in case new information occurs:

- **TA1:** Time series analysis
- **TA2:** Logistic regression
- **TA3:** Spearman correlation test

3.8 Expected Results

- **PA1**: Organizational changes in workplace regulations for HA- users. Enhance interventional strategies and regulation’s implementation in regards to hearing protection devices.
- **PA2**: Establishment of minimal technologies and communications standards for successful use of HAs by proving relationship between EVOTION technology and effectiveness of prevention and prognosis of noise induced hearing loss and reduce of disparities
- **PA3**: Ability of HL patients and clinicians using EVOTION technology to detect or prevent (further progress of) NIHL as fast as possible
- **PA4**: Establishment of effects of daily noise type and duration on trend of NIHL developing in patients with AT or not
- **PA5**: Update of tools available to clinicians based on results from the model

- **PA6**: Recognition of dangerous sources of situations depending on users’ activities and application of restrictions/warnings to such places for avoidance of potential patients in the general population.
- **PA7**: Development of the recommendation (rules) concerning employment of HAs' users in noisy occupational environments
- **PA8**: Evidence on the effectiveness of interventions designed to reduce or prevent workplace injuries and illnesses due to occupational NIHL.

4 PHPDM for Prognosis and Delivery of Effective Auditory Training Rehabilitation

4.1 Defining the Decision Model

The key reason underpinning ineffective HA use is that HAs are fitted to suit the audiogram rather than the patient's needs and overall profile. Ideally, HA fitting should be appropriately supported by rehabilitation treatments such as AT (i.e., listening exercises designed to improve the function of the auditory system), (Musiek et al., 2002), as HA users depend more on their cognitive resources than normal hearing listeners in order to understand speech (Moradi et al., 2014). As previously mentioned (Section 2.4) systematic reviews (Henshaw and Ferguson, 2013) and randomized clinical trials (Saunders et al., 2016) have indicated poor evidence for the effects of AT for adult HA users, except for some evidence for psychosocial support of AT in this population (Hickson et al., 2007) EVOTION will develop a prototype auditory training mobile app that will be made available to the patients for a period of twelve (12) months. This model aims to provide evidence for the identification of predictors of effective AT and how to link this information onto appropriate management strategies.

4.2 Basic Goals and Objectives

Goals

G1: Optimise HA use and benefit

G2: Delay cognitive and auditory processing deterioration

Objectives

O1: Study if AT could improve the multi-dimensional HA outcomes for patients with HL.

O2: Provide alternative support to people with HL.

4.3 Decision Criteria

Most AT programs for individuals with HL are organized taking into consideration three (3) parameters: auditory processing approach, auditory skill, and stimulus difficulty level.

CR1: Patients who receive AT versus those who do not, use HA 2 hours more than average daily or 3 days more than average monthly, over the first period of 3 months;

CR2: Patients who receive AT versus those who do not, score better at GHABP during the first 3 months following the AT

CR3: Patients who have received AT yearly versus those who do not, score better at MOCA measured in a year's time and over a 6-year period;

CR4: Patients who have received AT yearly versus those who do not, report a 15% lower listening effort over a 6-year period

CR5 Patients who receive AT show reduced listening effort (indexed by a computation of physiological measures/self-rated) compared to those who do not

CR6: Availability of time/funds required for AT

4.4 Evidence supporting the need for this PHPDM

Evidence is available that AT has potential to improve HA use/benefit. The present PHPDM could underpin this existing evidence and also study which type/dosage of AT would be most suitable for the purpose.

4.5 Correlation with EVOTION data

ED1: GHABP scores and HA use. These data can be found in:

- **GHABP_ANSWERS_N Table**
- **GHABP_ANSWERS Table**
- **GHABP_ RESULT Table**
- **GHABP_PROFILE Table**
- **GHABP_QUESTIONS Table**
- **GHABP_REF_DATA Table**
- **GHABP_SITUATIONS Table**
- **RETRO_HA Table**

ED2: MOCA score, listening effort. These data can be found in:

- **MOCA_ANSWERS Table**
- **RETRO_HA Table**

4.6 Factors affecting this PHPDM

AT Type (**F1**) and AT Dosage (**F2**), can be found in the **HEARING_COACH_TRAINING Table**.

Other types of data that might affect the model, but are outside of EVOTION's platform collecting capabilities, are the following:

- Concurrent use of HAs, mobile phones and apps.
- Patient education and engagement.
- Patients engaging with AT and adherence monitoring
- Patients returning for 6-month additional follow-up visits.

4.7 Types of Analysis

Identified types of analysis to be employed for this PHPDM include, but are subject to change in case new information occurs:

- **TA1**: Correlation analysis
- **TA2**: Analysis of variance (ANOVA)

4.8 Expected Results

- **PA1**: Assessment of current and EVOTION HA associated services effective in the reduction of hearing disability and handicap, using the outcome measures of GHAB part 1 and part 2 outcomes and comparing their results
- **PA2**: Implementation of guidelines introduced by EVOTION in different acoustic situations, through assessment of the performance of EVOTION HA technology and AT in listening situations (e.g. television, telephone, cinema, understanding speech in a group, radio or listening to music, understanding speech in a bus, train or car, understanding children's voices, having conversations with people when there is no background noise) by comparing the outcome measurement of Part 1 GHABP results performed during the first visit and the GHABP part 2 outcomes during the third visit, during this 6-week period.
- **PA3:** Assessment of the EVOTION technology impact on facilitating auditory/speech language and services at home training and influence of assistive devices on facilitating AT due to types of AT.
- **PA4:** Assessment of effect of AT and services on cognitive function due to workplace and social adaptation and due to primary symptom of HL.
- **PA5**: Reduced follow-up appointments for complaints, problems or difficulties with HA use.

5 PHPDM for Hearing Loss Management and Overall Well-being of Hearing Impaired Individuals

5.1 Defining the Decision Model

The consequences of HL in the overall health condition of the people suffering from it are significant. Several studies have shown that HL increases the risk of cognitive decline/dementia by 20% (Lin et al., 2011), mental illness (Matthews et al., 2013), depression (Davis, 2011; Matthews et al., 2013) and the risk of mortality (Holwerda et al., 2012), as a result of reduced physical and mental activity and social isolation (Arlinger, 2003). The latter factors also lead to an overall poorer quality of life, both in physical and mental terms (Arlinger, 2003). PHP can have a significant effect on, among others, the early detection, delay or even prevention of cognitive decline.

The model will address PHP decision making for HL treatment/rehabilitation in relation to the effect of HL on cognitive decline and its effect on well-being of individuals with HL.

5.2 Basic Goals and Objectives

Goals

G1 Identification of factors that predict cognitive decline, the reduction of cognitive decline after HA fitting or improved well-being in individuals with HL. Identification of cognitive decline related to HL would be a part of assessing improved cognitive status. This will provide further data to strengthen evidence of the link between cognitive decline and HL.

G2: Improved social activity and quality of life in individuals with HL.

Objectives

O1: Increased performance in cognitive tests deployed in the EVOTION platform

O2: Reduced cognitive decline, measured by performance in specific tests (e.g. MOCA)

O3: Increased social activity of HA users measured by data gathered in EVOTION

O4: Improved quality of life measured by specific tests (e.g. Health Utilities Index Mark 3, HUI3)

5.3 Decision Criteria

CR1: Reduced or improved MOCA or Digit Recall scores

CR2: Increase in outdoor/social activity of HA users

CR3: Clinically significant improvement in HUI3 health utility scores

5.4 Evidence supporting the need for this PHPDM

There is evidence that HL is independently associated with a 30-40% rate of accelerated cognitive decline (Lin et al., 2013) and individuals with mild, moderate or severe HL had a 2- 3- and 5-fold increased risk of incident all-causes dementia over a 1 year follow-up period (Lin and Albert, 2014). The auditory health trainings are necessary in the work environments, since the auditory health is important for the people's communicative and social process. However, the activities oriented to the promotion and prevention of changes in that area are still very limited. Moreover, the trainings and guidance to professionals within the public health level and in companies are necessary, since the teaching-learning process requires activities that emphasize the importance of detecting and preventing hearing changes (Ribeiro et al., 2014). Greater attention should also be given to improving lifestyle and medical risk factors for cognitive declines, which would help the prevention and mitigation of HL, in combination with other ways to promote healthy physical, mental, and social aging (Pichora-Fuller et al., 2015).

Evidence from EVOTION could be used to determine whether risk of cognitive decline causing dementia is related to hearing level, and whether public health interventions such as provision and use of hearing devices [and/or mind exercises] stop or reduce the rate of cognitive decline. This would have very large implications for development of public health policy and reduction of the burden of hearing disability in the population.

5.5 Correlation with EVOTION data

ED1: MOCA will be administered at baseline and at a six-eight weeks follow-up to screens for cognitive dysfunction. A forward and backward digit recall test will also be available to perform via the mobile app and can assess cognitive abilities such as working memory over a twelve-month period

ED2: HUI3, Scores provide a health-related quality of life index.

ED3: HA logging data, periods of HA usage;

The aforementioned data can be found:

- **MOCA_ANSWERS Table** (ED1)
- **HUI3_ANSWERS Table** (ED2)
- **TTSNIHL_TEST_RESULT Table** (ED1)
- **MOBILE_AUDIOMERY_RECORD Table** (ED1)

5.6 Factors affecting this PHPDM

The effect of hearing loss itself on cognitive load, brain structure, and decreased social engagement (**F1**) can be found in the **Q_DRMED Table**.

Co-morbidities such as diabetes, smoking, vascular disease, and other causes of cognitive decline or dementia all of which may act as confounding factors (e.g. occupation, educational attainment, age of onset of hearing loss) (**F2**) can be found in **PATIENT Table**.

Cognitive data (e.g. reading span of HA user, verbal reaction time-as an index of listening effort and cognitive load and types of errors in auditory communication, longitudinal mood monitoring, reverse digit recall measure of auditory working memory) (**F3**) can be found in **COGNITIVE_TEST_RESULT Table, MOCA_ANSWERS Table** and **HADS_ANSWERS Table.**

5.7 Types of Analysis

Identified types of analysis to be employed for this PHPDM include, but are subject to change in case new information occurs:

- **TA1**: Multiple linear regression,
- **TA2**: Correlation analysis.

5.8 Expected Results

Policy interventions could be:

- **PA1**: Provision of HAs and regular support and training to increase the frequency and effectiveness of HA usage
- **PA2**: Identification of resources to enforce collaboration between Ear Nose Throat experts (ENTs) and neurologists

For HA users with low scores on cognitive tests or deteriorating scores in cognitive tests

- **PA3:** Referrals to appropriate clinicians for assessment and recommendation of patient specific programmes for improving cognitive skills
- **PA4:** Social campaigning actions to increase patient awareness and inform them of remedies
- **PA5:** Provision of serious games applications that can improve cognitive skills

6 Demonstrator

6.1 Demonstrator background information

Exposure to excessive SPL may result in temporary or permanent deterioration of hearing. Avoiding situations where excessive exposure to noise increases the protection of the hearing system from damage. The monitoring of sound/noise exposure allows us to recognize the circumstances under which potentially harmful sound levels may occur. With the EVOTION platform this is accomplished by determining potential PTS/TTS episodes during usage of the HA device.

There are three combinations of possible outcomes for predicting PTS / TTS episodes, i.e.:

- Excessive SPL values outside the HA user's ear might cause PTS and TTS episodes
- High SPLs outside the HA user's ear are likely to cause TTS episodes
- Low SPLs outside the HA user's ear are unlikely to cause any hearing changes.

Depending on the outcomes of the evaluation of PTS / TTS episodes, appropriate preventive actions should be taken, e.g. informing the HA user about environment conditions or activities that may be a source of harmful exposure to noise. Sharing the sound exposure data with health care professionals allow them to counsel the user about their hearing habits, and finally combining the sound exposure data from many users enables public authorities to investigate health policy actions for noise exposure.

During the first stage of EVOTION, demonstrators rely on sound exposure from pilot users combined with available static clinical data. Later in EVOTION this will be transformed into predicting the noise exposure and PTS/TTS episodes for individuals using the EVOTION platform.

The first stage of the project concerns only the environmental sounds/noise measured at outside situations. Over the next deliverables (D3.2, D3.3) work, as well as sound/noise monitoring will also refine the modeling and improve the prediction of SPLs at ear drum. This will allow individualized prediction of PTS / TTS episodes due to the ambient sounds processed by the HA device.

6.2 Demonstrator Goals

In this demonstrator, the goal is to produce generate a PTS/TTS alert in the EVOTION platform, to undertake appropriate intervention actions related to the aforementioned events. For this purpose, static clinical data (i.e. audiograms) from *NIOSH Dataset SD-1001-2014-0, Prevalence of Hearing Loss in the United States by Industry*, developed by NIOSH Occupational Hearing Loss Surveillance Project, Division of Surveillance, Hazard Evaluations and Field Studies, will be used. For more information, readers are referred to (Masterson et al., 2014) and download at the NIOSH website. The NIOSH dataset contains more than one million audiograms from collected between 2000 and 2008 from individuals working in industries in US with higher occupational noise exposures than the general population (Masterson et al., 2014).

6.3 Demonstration Scenario Steps

Let us assume that we want to check the possibility of TTS episodes for attendees with HL at a rock concert placed in the middle of the attendants. Let us also assume that a PHP maker involved in the EVOTION, is interested in finding out on whether such an event has an effect on the PTS/TTS episodes on these users.

Per the model description, one has to define the goal (G)/objective (O) he or she wishes to explore (Section 3.2). In our case, the goal is:

- **G3:** Prevention and decrease of TTS episodes

with the objective:

- **O1**: Development of model for PTS/TTS prediction based on cumulative individuals' activities data

The criterion (Section 3.4) to be applied in our case is:

- **CR1**: PTS/TTS episodes associated with high external sound levels require intervention for training in the use of HA in a noisy environment.

The EVOTION Data (Section 3.5) we are supposed to use are to be taken from the **REAL_TIME_HA** Table, and more specifically from the columns named **PATIENT_ID**, **S_PARA** and **S_EN_PARA**. The factor that might affect the model, is the daily time HA usage pattern (**F2**), which can also be found in the **REAL_TIME_HA Table**, in the **PRO_USAGE** column. However, since the aforementioned data are not currently available at the EVOTION Data Repository, we have to create a data file that contains data in the same format that they will be saved to the Repository.

Since the static data taken from the NIOSH dataset are not available in the EVOTION dataspace, they need to undergo (a) preprocessing to be in a format fitting the concept of EVOTION and (b) adjustment due to missing values, which are assumed to be zero (0).

These are further processed, being encapsulated into data coming from a real-time recording performed by EVOTION HAs during a rock concert. The goal of the aforementioned procedure is to create a simulated pool of rock concert attendees with HL problems to evaluate the performance of the model described in Section 3. As the definition and correct format of the model is part of an upcoming deliverable (D4.1), the whole procedure of applying the model on these data has been thoroughly described:

The static clinical data from the NIOSH dataset are split into positions at the venue (c.f. Figure 3Figure 3):

- Front row group (Quarter distance from the recording site)
- Front group (Half distance from the recording site)
- Middle group (Close to the recording site)

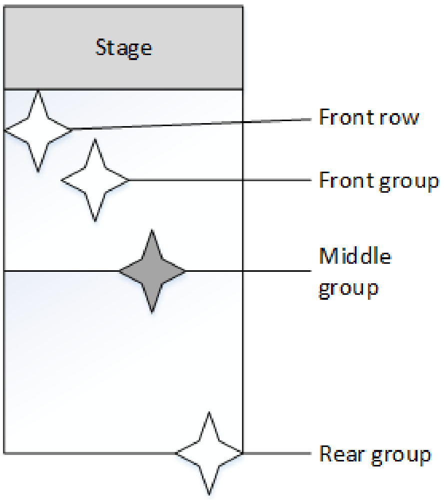

Figure 3: Concert venue

- Rear group (Double distance from the recording site)

The simulation assumes an outdoor venue and with public address and loudspeakers positioned at the front of the stage.

For the individual static clinical data the modeling the HA amplification is half-gain with compression that reduces amplification for loud sounds.

The type of analysis to be used (Section 3.7) is set to **TA2**: Logistic Regression, which can be used to analyse a dataset in which there are one or more independent variables that determine an outcome (TTS episodes in our case).

6.4 Results

Simulating the TTSs for a large population of individual HLs from the NIOSH data set produces Figure 4 and Figure 5.

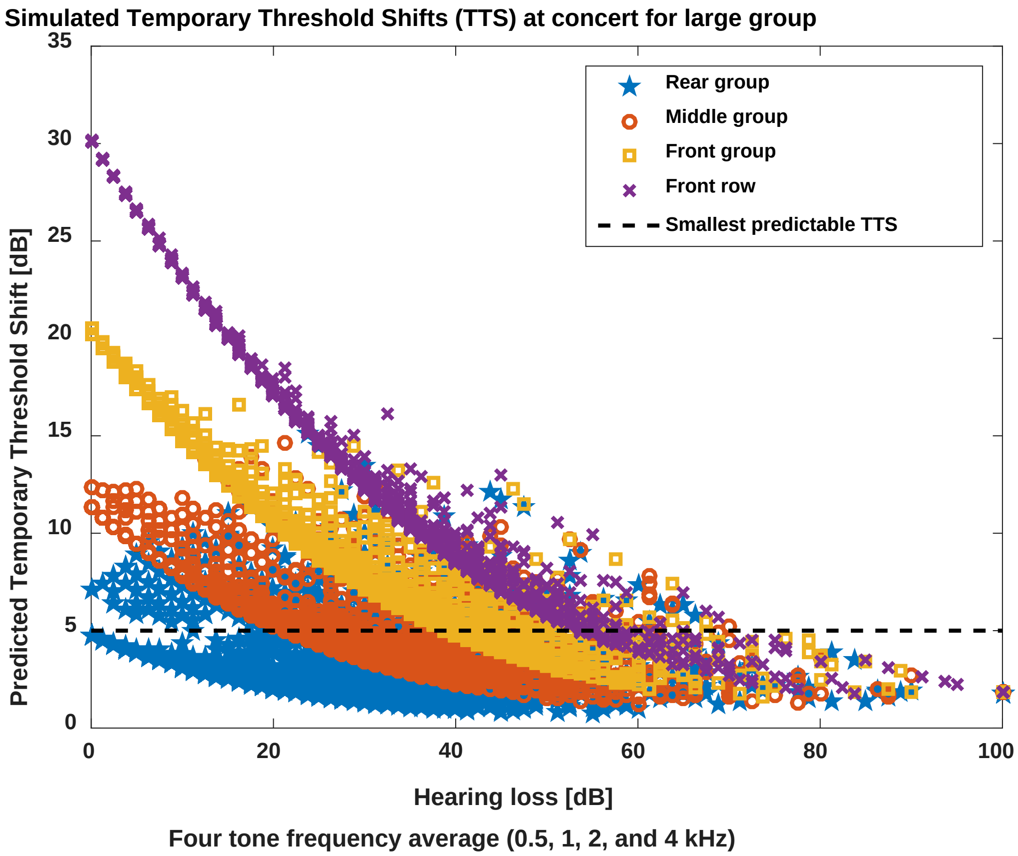

Figure 4 Simulated TTS for concert attendees with HL (NIOSH dataset) as function of HL

The simulation output in Figure 4 shows the TTS for all the attendees as function of the HL. One overall trend is that the amount of TTS decreases as function of the HL – this is due to the output limiting of the amplification that ensures that loud sounds are not amplified as much as weak sounds. However, there seems to be a large variation in the TTS outcome for the Rear group, and in fact decreasing variation in TTS outcome as the positioning moves towards the stage.

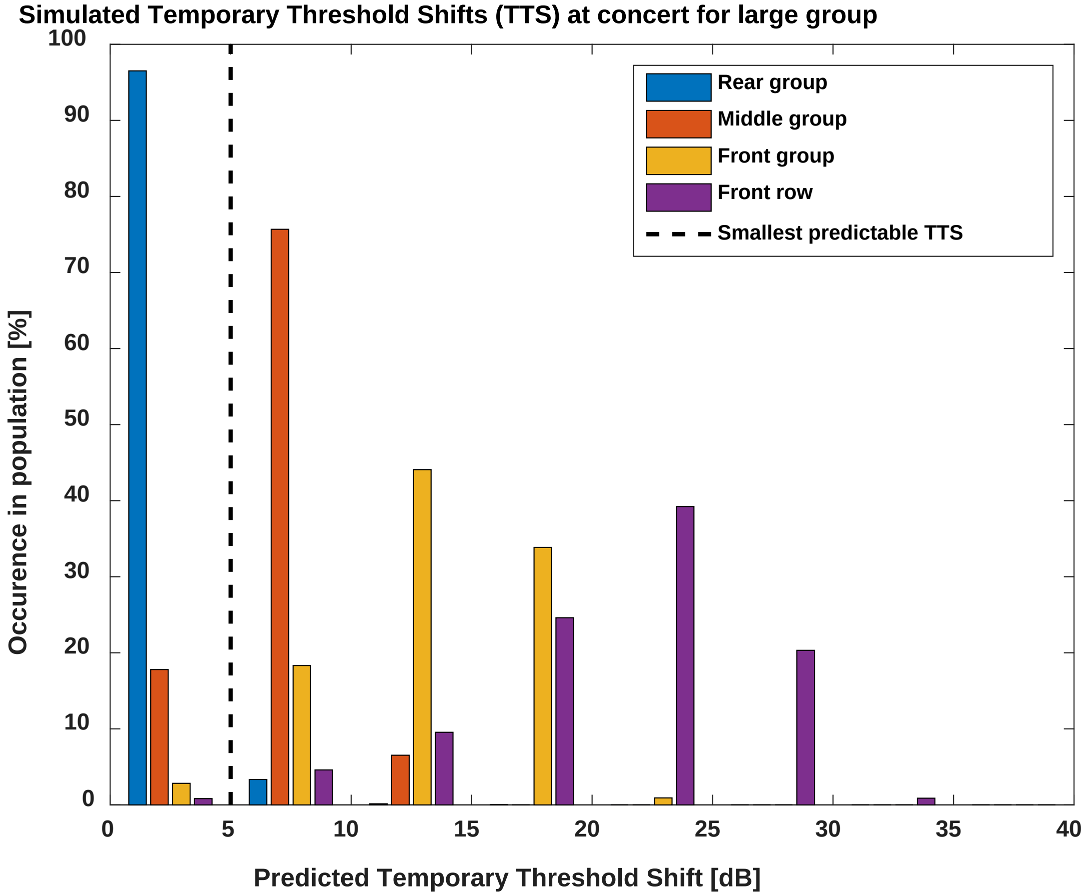

Figure 5 Normalized histogram for simulated TTS for the NIOSH dataset

The normalized TTS histogram (Figure 5) shows the distribution of TTS as function of the position, which follows directly from the assumption that moving towards the sound source increases the sound level (holds for direct sound fields and do not hold for indoor sound). Moreover, the figure shows that seemingly large variation of the Rear Group TTS is in fact quite small as less than 5% of the Rear Group TTS values exceed 5 dB TTS.

The results shown in Figure 4 and Figure 5 indicate:

- That for all the attendees in the front half, the excess sound they are exposed to causes TTS
- That HL and modern HA amplification that do not amplify loud sounds do not causing excess TTS and HL
- Any means of attenuating the sound limits the TTS and thus the impact on the individual hearing

The whole data analysis took approximately 4 min (run on an Intel ® Core™ i7-6700HQ CPU @ 2.60 Ghz, 16 GB RAM, Microsoft™ Windows 10 x64, NVIDIA GEFORCE® GTX 1070) with the Mathworks® Matlab software, available from https://www.mathworks.com/products/matlab.html. The total performance time as well the self-time (time spent in a function excluding the time spent in its child functions, including overhead resulting from the process of profiling) of the most "demanding" functions are shown in Figure 6.

Generated 31-Oct-2017 14:18:48 using performance time.

Function Name	Calls	**Total Time**	Self Time*
evotion_d31_tts_predict_demo_bd	1	194.367 s	12.129 s
evotion_d31_tts_predict	200004	128.670 s	128.670 s
evotion_d31_genericgain	200004	25.445 s	25.445 s
str2num	350007	19.523 s	5.666 s
str2num>protected_conversion	350007	13.858 s	13.858 s
mean	200004	3.158 s	3.158 s
fgetl	50003	1.658 s	1.658 s
evotion_d31_tts_predict_HL	200004	1.218 s	1.218 s
saveas	2	1.131 s	0.009 s
general\private\saveasfig	2	1.117 s	0.001 s
savefig	2	1.116 s	0.084 s
legend	2	0.508 s	0.011 s
legend>make_legend	2	0.464 s	0.013 s
Legend.doMethod	35	0.445 s	0.008 s

Figure 6 Performance of Demonstrator Functions

Given the costs of those incidents, a policy could investigate the cost benefit of mandatory hearing protectors at concert venues, especially in relation to the cost of supplying such hearing protectors. Therefore, these results could lead to relevant policy actions PA3-PA6 as defined in Section 3.8.

6.5 Accessibility of demonstrator

In order to access the materials, readers are prompted to do the following:

1. Visit the EVOTION Deliverable page at http://h2020evotion.eu/deliverables
2. A video showing the successful running of the demonstrator can be downloaded from URL: http://h2020evotion.eu/?ddownload=508 .
3. The Matlab/Octave code to demonstrate the processing of data can be downloaded from URL: http://h2020evotion.eu/?ddownload=507.

6.6 Example Installation of Octave and Instructions (For testing purposes)

Materials have been uploaded on 31 October 2017 to the EVOTION website (www.h2020evotion.eu). The following list provides an overview of the files, required for a successful run of the demonstrator:

• evotion_d31_tts_predict_demo_bd.m	file	main file
• evotion_d31_tts_predict.m	file	auxiliary function
• evotion_d31_testdata.m	file	auxiliary function
• evption_d31_genericgain.m	file	auxiliary function
• evotion_d31_tts_predict_HL.m	file	auxiliary function

The audiograms from (Masterson et al., 2014) must be be downloaded from the NIOSH website:

• data.csv file	file	audiogram data

Prior to running the demonstrator, the Octave (https://www.gnu.org/software/octave/) freeware should be installed. After successful installation of the software, the downloaded files should be put into the same folder (e.g. evotion_d31_demo). In order for the demonstrator to run without any problems, line 27 in the *evotion_d31_tts_predict_demo_bd.m* file should be rewritten to point to the data.csv file (e.g. if you have created a folder named 'evotion_d31_demo' in your desktop, then line 27 should be changed to:

```
fid=fopen('C:\Users\...\Desktop\evotion_d31_demo\data.csv','r');
```

After the aforementioned steps, open Octave and point the File Browser to the demonstrator folder (Steps 1-4 as shown in Figure 7) leading to what is shown in Figure 8. After that, select the file of the evotion_d31_tts_predict_demo_bd and run it (Figure 9). Successful running should produce the diagrams shown in Section 6.4 Results.

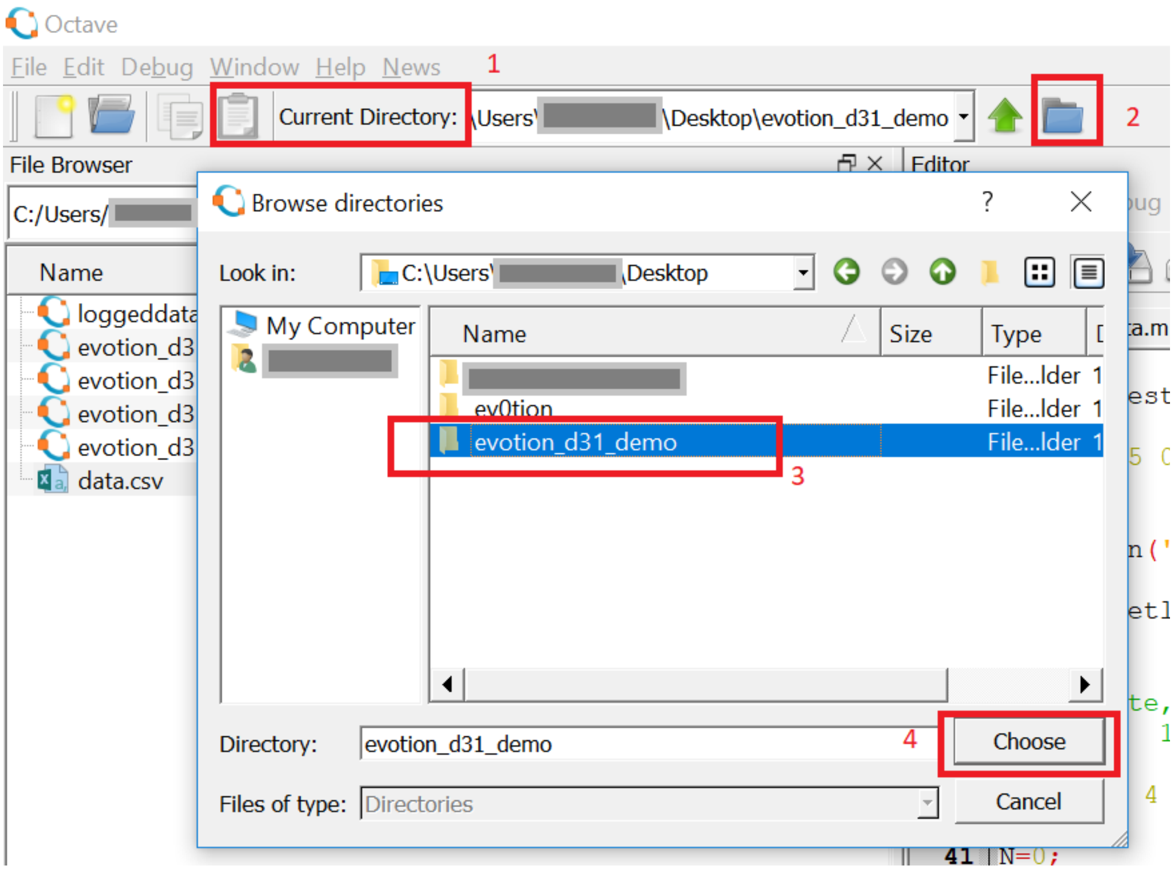

Figure 7 Octave Screen showing successful steps for setup

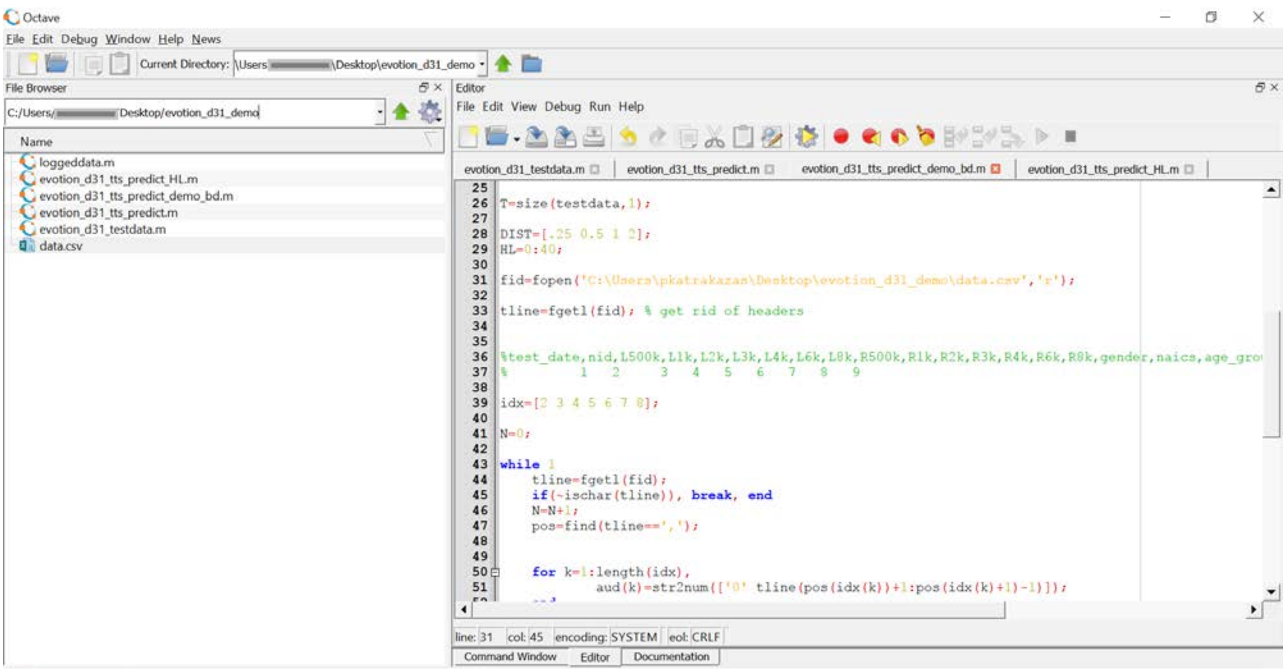

Figure 8 Octave Screen showing successful setup prior to running the demonstrator

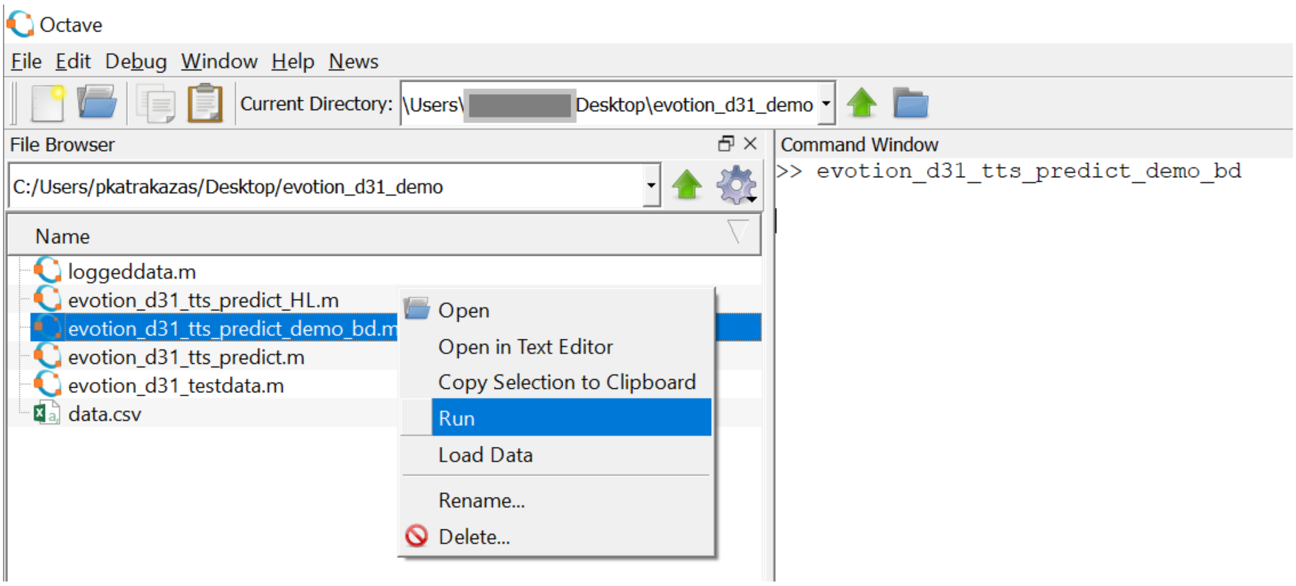

Figure 9 Selection and Running of the evotion_d31_tts_predict_demo_bd file

When the evotion_d31_tts_predict_demo_bd function completes, it will have produced two figures: TTS for individuals as function of hearing loss (c.f. Figure 4) and the normalized histogram of TTS for the same individuals (c.f. Figure 5).

7 Concluding Remarks

This report presents a first attempt at the development of four (4) novel decision models informed by big data analytics to support decisions related to policy making in key HL treatment and management areas.

The models described in the current report specified the generic goal(s) underpinning the decisions to be made, the criteria to be used for making such decisions, the evidence required for applying those criteria and the big data analytics processes for producing it, along with the PHP actions to be followed. The report is complemented by a video demonstrating a specific scenario based on the Prognosis and Prevention of Noise Induced Hearing Loss model along with the source code used to prepare the video. As a whole this demonstrates the potential by introducing such models in the PHP domain.

There were four (4) PHPDMs described in this report:

- Prognosis of Effectiveness of HA Usage (PHPDM1),
- Prognosis and Prevention of Noise Induced Hearing Loss (PHPDM2),
- Prognosis and Delivery of Effective Auditory Training Rehabilitation Services (PHPDM3) and
- Hearing Loss Treatment/Overall Well-being of Hearing Impaired Individuals (PHPDM4).

The following figures (Fig. 10-13) show an overview of the key points in each PHPDM, excluding deliberately the EVOTION Data and Factors at this point:

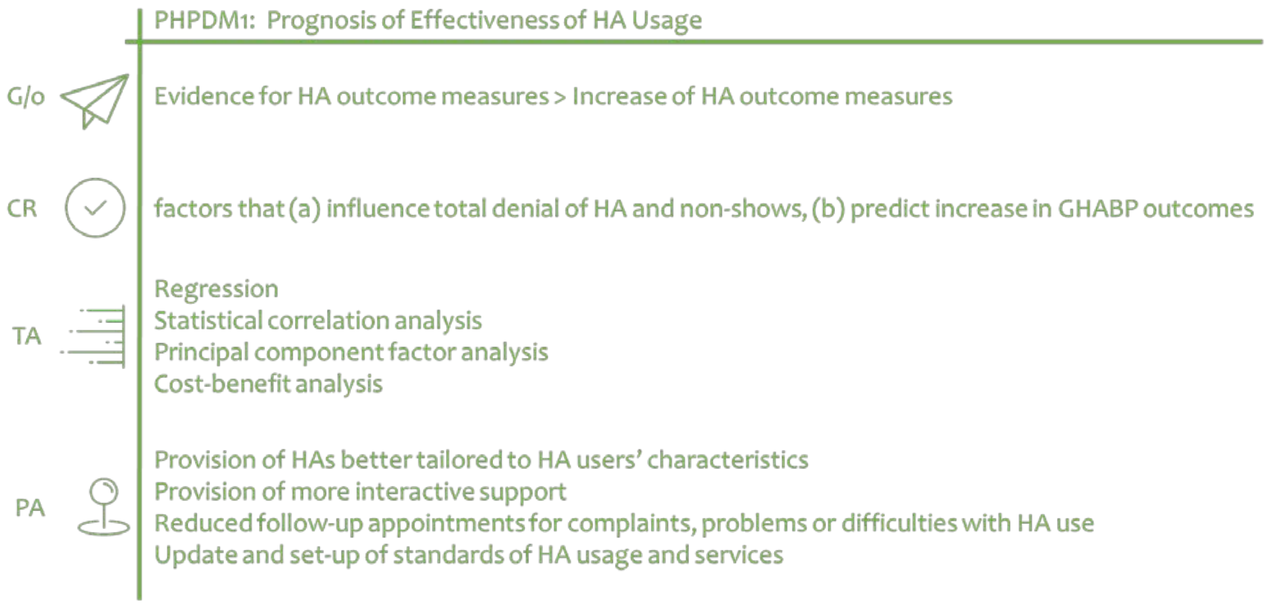

Figure 10 PHPDM1 Key points

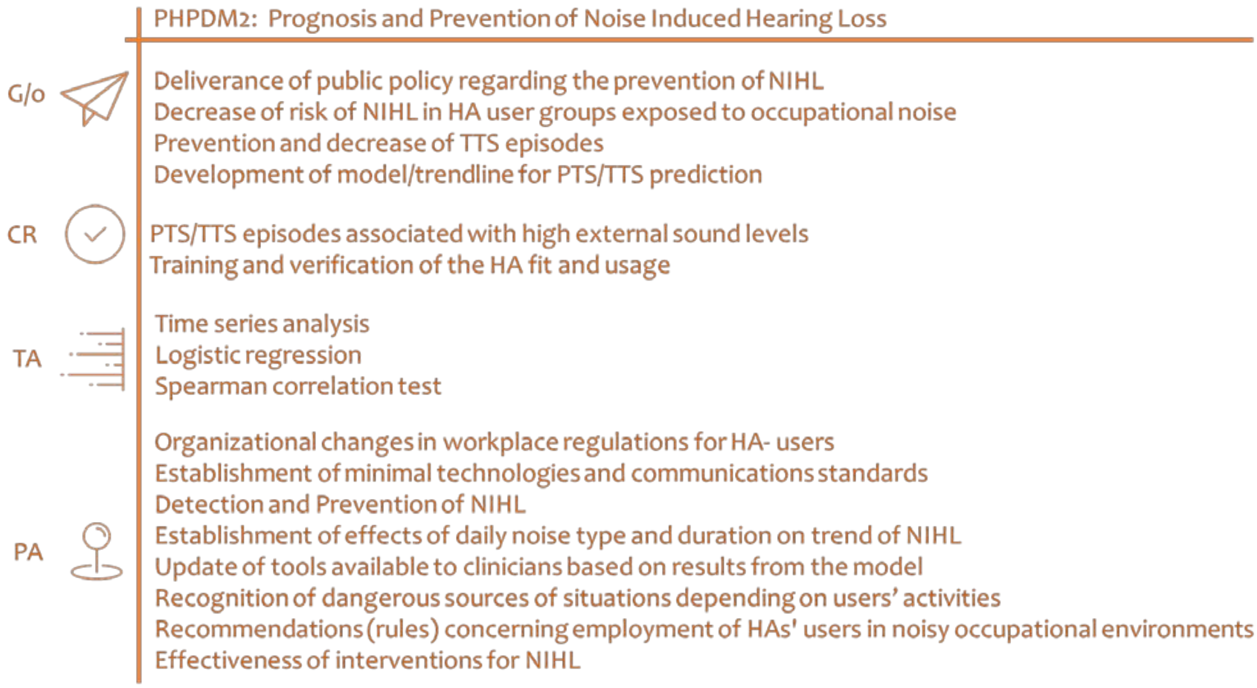

Figure 11 PHPDM2 Key points

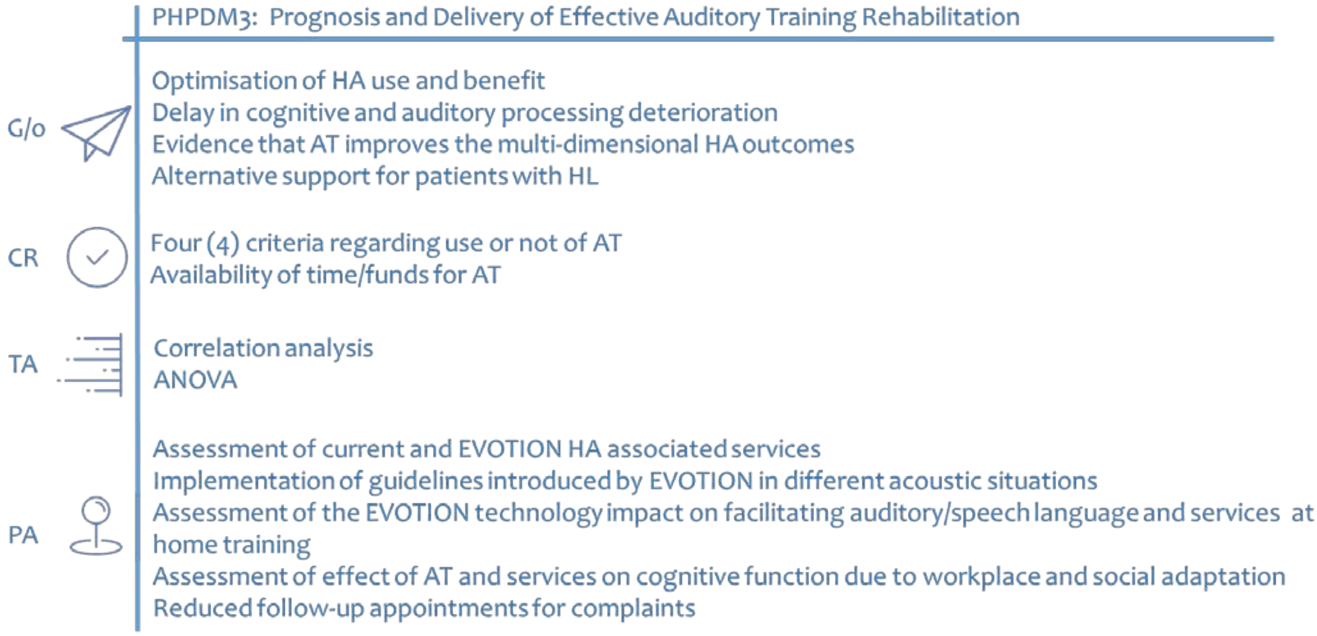

Figure 12 PHPDM3 Key points

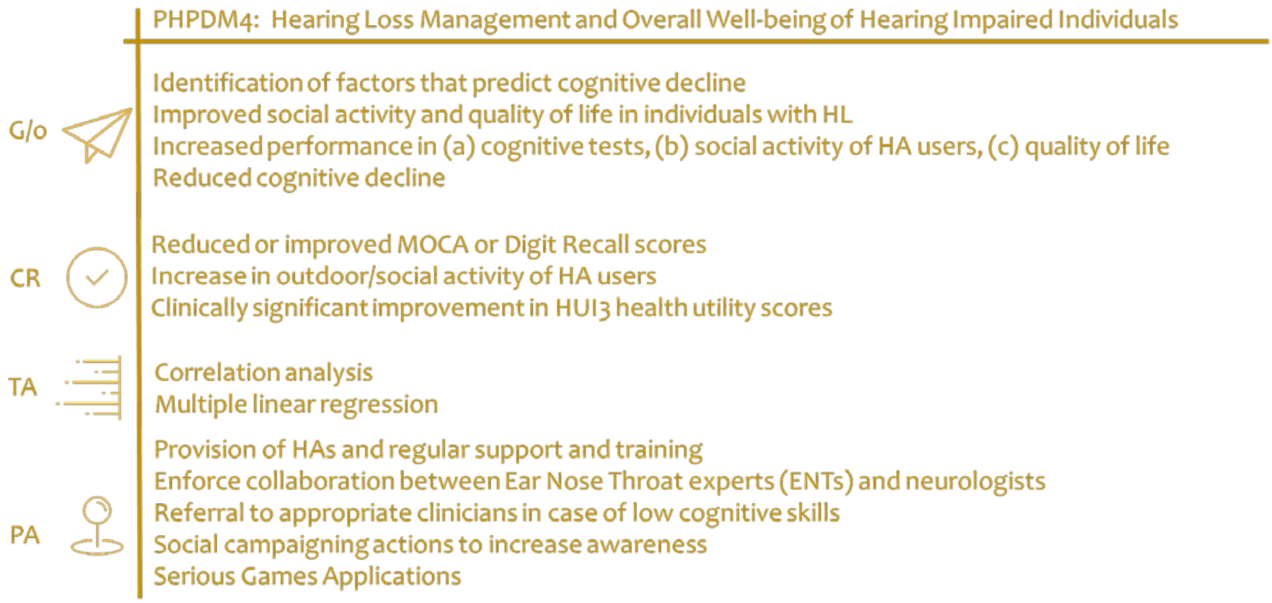

Figure 13 PHPDM4 Key points

These models are described by their building elements defined in the report as Goals, Objectives, Type of Analysis and Policy Actions.

The most significant outcome of this deliverable's report, however, is the introduction of the EVOTION dataspace (EVOTION Data and Factors) in the aforementioned models, which has a great impact as shown in Figure 14.

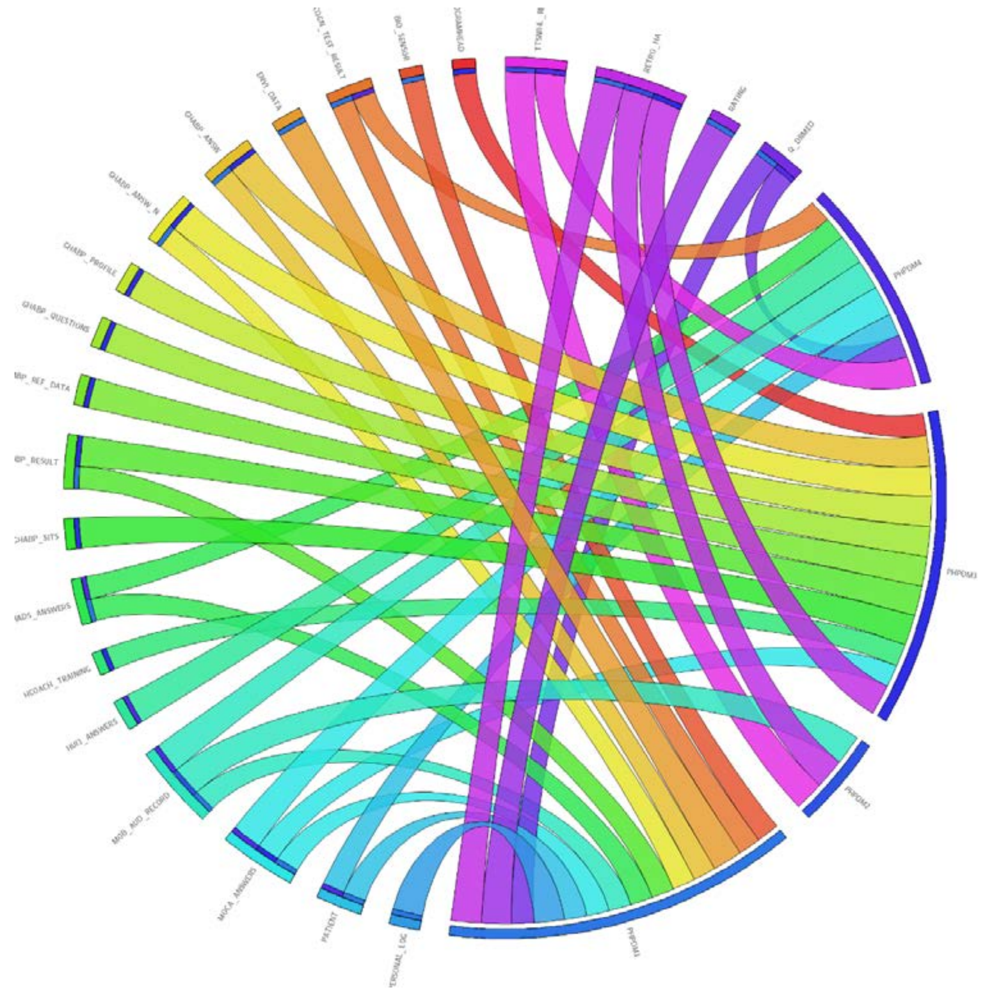

Figure 14 EVOTION Dataspace and Confirmed Interconnections with PHPDMs

PHPDM as shown in the previous figures (Fig. 10-13) can be decomposed to their basic elements, however it is the introduction of the EVOTION datasets that pinpoint the basic variables needed for each model. These connections work not only at a data, but at a PHP level as well, as it is indicated that datasets might affect more than one PHPDMs and vice versa (Figure 14). Thus providing PHP makers with further evidence that can assist the policy formulation via a visualization of data relationships into existing models, empowers their position as decision makers and allows them to test more hypotheses at a public health policy level. The selected demonstration scenario based on PHPDM2 explores the potential presented by introducing such models in the PHP domain.

The PHPDMs presented in this report is in an advanced, yet pre-final version. The delivered version contains the necessary building structures sufficient for translating the same models in the language developed in Work Package 4.

The EVOTION PHPDMs are to be extended in the subsequent phase of the project, incorporating phases (iii) initial pattern recognition, (iv) feature selection and dimensionality reduction, (v) development of the optimal prediction model and (vi) finalization of the PHPDMs. As planned, these parts will be explored over and finalized in the next two deliverables of WP3 (D3.2 and D3.3)(c.f. Figure 1).

References

Arlinger, S., 2003. Negative consequences of uncorrected hearing loss–a review. Int. J. Audiol. 42 Suppl 2, 17–20.

Azur, M.J., Stuart, E.A., Frangakis, C., Leaf, P.J., 2011. Multiple imputation by chained equations: what is it and how does it work? Int. J. Methods Psychiatr. Res. 20, 40–49. doi:10.1002/mpr.329

Barbosa, M.R., Medeiros, D. de S., Ribeiro, G.M., Rossi-Barbosa, L.A.R., Caldeira, A.P., 2013. Satisfaction with hearing aids among users of hearing health services. Audiol. - Commun. Res. 18, 260–267. doi:10.1590/S2317-64312013000400006

Barker, F., Mackenzie, E., Elliott, L., Jones, S., de Lusignan, S., 2014. Interventions to improve hearing aid use in adult auditory rehabilitation. Cochrane Database Syst. Rev. CD010342. doi:10.1002/14651858.CD010342.pub2

Barrigón Morillas, J.M., Montes González, D., Rey Gozalo, G., 2016. A review of the measurement procedure of the ISO 1996 standard. Relationship with the European Noise Directive. Sci. Total Environ. 565, 595–606. doi:10.1016/j.scitotenv.2016.04.207

Basdekis, I., Ye, B., Spanoudakis, G., Dimakopoulos, N., Kokkinakis, Panagiotis, Smyrlis, M., Katrakazas, P., Pontoppidan, N.H., 2017. Data Repository and Collection Components, Confidential Deliverable D5.2 to the EVOTION-727521 Project funded by the European Union. CITY University, London, United Kingdom.

Bentler, R., Mueller, H.G., Ricketts, T.A., 2016. Modern Hearing Aids: Verification, Outcome Measures, and Follow-up. Plural Publishing.

Bernhardt, J.M., Mays, D., Kreuter, M.W., 2011. Dissemination 2.0: closing the gap between knowledge and practice with new media and marketing. J. Health Commun. 16 Suppl 1, 32–44. doi:10.1080/10810730.2011.593608

Borg, J., Larsson, S., Östergren, P.-O., Rahman, A.A., Bari, N., Khan, A.N., 2012. User involvement in service delivery predicts outcomes of assistive technology use: A cross-sectional study in Bangladesh. BMC Health Serv. Res. 12, 330. doi:10.1186/1472-6963-12-330

Brownson, R.C., Fielding, J.E., Maylahn, C.M., 2009. Evidence-Based Public Health: A Fundamental Concept for Public Health Practice. http://dx.doi.org/10.1146/annurev.publhealth.031308.100134.

Czyzewski, A., Kotus, J., Kostek, B., 2007. Determining the noise impact on hearing using psychoacoustical noise dosimeter. Arch. Acoust. 32, 215–29.

Davis, A., 2011. National Survey of Hearing and Communication. UK.

Dillon, H., 2012. Hearing Aids, 2nd edition. ed. Thieme Medical Publishers, Dunn.

Gelman, A., Hill, J., 2007. Data Analysis Using Regression and Multilevel/Hierarchical Models. Cambridge University Press.

Guo, T., Kutzkov, K., Ahmed, M., Calbimonte, J.-P., Aberer, K., 2016. Efficient Distributed Decision Trees for Robust Regression. Eur. Conf. Mach. Learn. Princ. Pract. Knowl. Discov. Databases ECML-PKDD.

Heesterbeek, H., Anderson, R.M., Andreasen, V., Bansal, S., De Angelis, D., Dye, C., Eames, K.T.D., Edmunds, W.J., Frost, S.D.W., Funk, S., Hollingsworth, T.D., House, T., Isham, V., Klepac, P., Lessler, J., Lloyd-Smith, J.O., Metcalf, C.J.E., Mollison, D., Pellis, L., Pulliam, J.R.C., Roberts, M.G., Viboud, C., Isaac Newton Institute IDD Collaboration, 2015. Modeling infectious disease dynamics in the complex landscape of global health. Science 347, aaa4339. doi:10.1126/science.aaa4339

Henshaw, H., Ferguson, M.A., 2013. Efficacy of Individual Computer-Based Auditory Training for People with Hearing Loss: A Systematic Review of the Evidence. PLOS ONE 8, e62836. doi:10.1371/journal.pone.0062836

Hickson, L., Worrall, L., Scarinci, N., 2007. A Randomized Controlled Trial Evaluating the Active Communication Education Program for Older People with Hearing Impairment. Ear Hear. 28, 212–230. doi:10.1097/AUD.0b013e31803126c8

Holwerda, T., Beekman, A.T.F., Deeg, D.J.H., Stek, M.L., van Tilburg, T.G., Visser, P.J., Schmand, B., Jonker, C., Schoevers, R.A., 2012. Increased risk of mortality associated with social isolation in older men: only when feeling lonely? Results from the Amsterdam Study of the Elderly (AMSTEL). Psychol. Med. 42, 843–53. doi:10.1017/S0033291711001772

Humes, L.E., Jesteadt, W., 1991. Modeling the interactions between noise exposure and other variables. J. Acoust. Soc. Am. 90, 182–188.

ISO 1999:2013, 2013. Acoustics -- Estimation of noise-induced hearing loss, 3rd ed.

Keidser, G., Dillon, H., Flax, M., Ching, T., Brewer, S., 2011. The NAL-NL2 Prescription Procedure. Audiol. Res. 1. doi:10.4081/audiores.2011.e24

Kemm, J., 2006. The limitations of “evidence-based” public health. J. Eval. Clin. Pract. 12, 319–324. doi:10.1111/j.1365-2753.2006.00600.x

Klein, R., 2003. Evidence and policy: interpreting the Delphic oracle. J. R. Soc. Med. 96, 429–431.

Knudsen, L.V., Öberg, M., Nielsen, C., Naylor, G., Kramer, S.E., 2010. Factors Influencing Help Seeking, Hearing Aid Uptake, Hearing Aid Use and Satisfaction With Hearing Aids: A Review of the Literature. Trends Amplif. 14, 127–154. doi:10.1177/1084713810385712

Kochkin, S., 2014. A comparison of consumer satisfaction, subjective benefit, and quality of life changes associated with traditional and direct-mail hearing aid use. Hear. Rev. 21(1), 16–26.

Kujawa, S.G., Liberman, M.C., 2009. Adding Insult to Injury: Cochlear Nerve Degeneration after “Temporary” Noise-Induced Hearing Loss. J. Neurosci. 29, 14077–14085. doi:10.1523/JNEUROSCI.2845-09.2009

Kuntz, K., Sainfort, F., Butler, M., Taylor, B., Kulasingam, S., Gregory, S., Mann, E., Anderson, J.M., Kane, R.L., 2013. Overview of Decision Models Used in Research. Agency for Healthcare Research and Quality (US).

Lin, F.R., Albert, M., 2014. Hearing Loss and Dementia – Who’s Listening? Aging Ment. Health 18, 671–673. doi:10.1080/13607863.2014.915924

Lin, F.R., Metter, E.J., O’Brien, R.J., Resnick, S.M., Zonderman, A.B., Ferrucci, L., 2011. Hearing loss and incident dementia. Arch. Neurol. 68, 214–20. doi:10.1001/archneurol.2010.362

Lin, F.R., Yaffe, K., Xia, J., Xue, Q.-L., Harris, T.B., Purchase-Helzner, E., Satterfield, S., Ayonayon, H.N., Ferrucci, L., Simonsick, E.M., 2013. Hearing loss and cognitive decline in older adults. JAMA Intern. Med. 173, 293–9. doi:10.1001/jamainternmed.2013.1868

Lindsey, L.L.M., Yun, K.A., 2003. Examining the persuasive effect of statistical messages: A test of mediating relationships. Commun. Stud. 54, 306–321. doi:10.1080/10510970309363288

Lofgren, E.T., Halloran, M.E., Rivers, C.M., Drake, J.M., Porco, T.C., Lewis, B., Yang, W., Vespignani, A., Shaman, J., Eisenberg, J.N.S., Eisenberg, M.C., Marathe, M., Scarpino, S.V., Alexander, K.A., Meza, R., Ferrari, M.J., Hyman, J.M., Meyers, L.A., Eubank, S., 2014. Opinion: Mathematical models: A key tool for outbreak response. Proc. Natl. Acad. Sci. 111, 18095–18096. doi:10.1073/pnas.1421551111

Macrae, J.H., 1995. Temporary and permanent threshold shift caused by hearing aid use. J. Speech Hear. Res. 38, 949–959.

Macrae, J.H., 1994a. An investigation of temporary threshold shift caused by hearing aid use. J. Speech Hear. Res. 37, 227–237.
Macrae, J.H., 1994b. Prediction of asymptotic threshold shift caused by hearing aid use. J. Speech Hear. Res. 37, 1450–1458.
Macrae, J.H., 1991a. Prediction of deterioration in hearing due to hearing aid use. J. Speech Hear. Res. 34, 661–670.
Macrae, J.H., 1991b. Permanent threshold shift associated with overamplification by hearing aids. J. Speech Hear. Res. 34, 403–414.
Masterson, E.A., Tak, S., Themann, C.L., Wall, D.K., Groenewold, M.R., Deddens, J.A., Calvert, G.A., 2014. Prevalence of Hearing Loss in the United States by Industry. Am. J. Ind. Med. 56, 670–681.
Matthews, F.E., Arthur, A., Barnes, L.E., Bond, J., Jagger, C., Robinson, L., Brayne, C., Medical Research Council Cognitive Function and Ageing Collaboration, 2013. A two-decade comparison of prevalence of dementia in individuals aged 65 years and older from three geographical areas of England: results of the Cognitive Function and Ageing Study I and II. Lancet Lond. Engl. 382, 1405–1412. doi:10.1016/S0140-6736(13)61570-6
Mazur, K., Voix, J., 2013. Implementing 24-hour in-ear dosimetry with recovery. Proc. Meet. Acoust. 19, 040016. doi:10.1121/1.4800398
McCormack, A., Fortnum, H., 2013. Why do people fitted with hearing aids not wear them? Int J Audiol 52, 360–8. doi:10.3109/14992027.2013.769066
Melnick, W., 1991. Human temporary threshold shift (TTS) and damage risk. J. Acoust. Soc. Am. 90, 147–154.
Mills, J.H., Gilbert, R.M., Adkins, W.Y., 1979. Temporary threshold shifts in humans exposed to octave bands of noise for 16 to 24 hours. J. Acoust. Soc. Am. 65, 1238–1248. doi:10.1121/1.382791
Moradi, S., Lidestam, B., Hällgren, M., Rönnberg, J., 2014. Gated auditory speech perception in elderly hearing aid users and elderly normal-hearing individuals: effects of hearing impairment and cognitive capacity. Trends Hear. 18, 1–12. doi:10.1177/2331216514545406
Musiek, F.E., Shinn, J., Hare, C., 2002. Plasticity, Auditory Training, and Auditory Processing Disorders. Semin Hear 23, 263–76. doi:10.1055/s-2002-35862
Nelson, D.I., Nelson, R.Y., Concha-Barrientos, M., Fingerhut, M., 2005. The global burden of occupational noise-induced hearing loss. Am. J. Ind. Med. 48, 446–458. doi:10.1002/ajim.20223
Orton, L., Lloyd-Williams, F., Taylor-Robinson, D., O'Flaherty, M., Capewell, S., 2011. The Use of Research Evidence in Public Health Decision Making Processes: Systematic Review. PLoS ONE 6. doi:10.1371/journal.pone.0021704
Pichora-Fuller, M.K., Mick, P., Reed, M., 2015. Hearing, Cognition, and Healthy Aging: Social and Public Health Implications of the Links between Age-Related Declines in Hearing and Cognition. Semin. Hear. 36, 122–139. doi:10.1055/s-0035-1555116
Ribeiro, G.M., Figueiredo, M.F.S., Rossi-Barbosa, L.A.R., Ribeiro, G.M., Figueiredo, M.F.S., Rossi-Barbosa, L.A.R., 2014. The importance of auditory health training: an integrative review. Rev. CEFAC 16, 1318–1325. doi:10.1590/1982-021620148513
Rossing, T., 2015. Springer Handbook of Acoustics. Springer.
Saunders, G.H., Smith, S.L., Chisolm, T.H., Frederick, M.T., McArdle, R.A., Wilson, R.H., 2016. A Randomized Control Trial: Supplementing Hearing Aid Use with Listening and

Communication Enhancement (LACE) Auditory Training. Ear Hear. 37, 381–396. doi:10.1097/AUD.0000000000000283
Seadle, M., 2016. Quantifying Research Integrity. Morgan & Claypool Publishers.
Sliwinska-Kowalska, M., Davis, A., 2012. Noise-induced hearing loss. Noise Health 14, 274. doi:10.4103/1463-1741.104893
Stef van Buuren, 2012. Multiple imputation, in: Flexible Imputation of Missing Data, Chapman & Hall/CRC Interdisciplinary Statistics Series. Chapman and Hall/CRC, pp. 25–52. doi:10.1201/b11826-4
Trenkova, L., Spanoudakis, G., Laplante-Lévesque, A., Smith, A., Milas, J., Brdarić, D., 2017. Decision modelling in Public Health Policy-making: EVOTION and Hearing Loss, in: Data 2017. Presented at the Data 2017, London.
Ye, B., Spanoudakis, G., Prasinos, M., Dimakopoulos, N., Kokkinakis, P., Giotis, G., Papas, I., Papagrigoriou, P., Smyrlis, M., Stefanakis, M., Katrakazas, P., Koutsouris, D., Brdaric, D., Pandzic, Z., Salavarda, D., Urban, M., Milas, J., Pontoppidan, N.H., Trenkova, L., Kaloyanova, G., Tsokova, N., Anisetti, M., Bellandi, V., Cremonini, M., Damiani, E., 2017. EVOTION Architecture and Detailed Design, Deliverable D2.2 to the EVOTION-727521 Project funded by the European Union. CITY University, London, United Kingdom.