727521 – EVOTION

DELIVERABLE No: D5.6

Decision Support System and Simulation Component

Author(s): Panagiotis Katrakazas, Apostolis Mpostanis (ICCS), Jeppe Høy Christensen (OTC)

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	R+DEM, Report and Demonstrator, pilot, prototype
Delivery date	M20 (30 June 2018)
Authors/contributors:	Panagiotis Katrakazas, Apostolis Mpostanis, (ICCS), Jeppe Høy Christensen (OTC) Reviewed by: Andrew Smith (CITY), Lyubov Trenkova (PRA), Ioannis Kouris, Dimitrios Koutsouris (ICCS)
Contact:	Panagiotis Katrakazas (pkatrakazas@biomed.ntua.gr)
To be cited as:	Katrakazas, P et al (2018), Decision Support System and simulation component, Deliverable D5.6 to the EVOTION-727521 Project funded by the European Union, ICCS, Greece
Subject and keywords:	This report presents the Decision Support System and simulation component of the EVOTION project Decision support system, text mining, model comparison and simulation, public health policy decision making
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

API	APPLICATION PROGRAMMING INTERFACE
BDA	BIG-DATA ANALYTICS
CLIS	CLINICAL INTERVENTION SCENARIO
DOA	DESCRIPTION OF ACTION
DSS	DECISION SUPPORT SYSTEM
DTM	DOCUMENT-TERM MATRIX
ECDSA	ELLIPTIC CURVE DIGITAL SIGNATURE ALGORITHM
ED	EVOTION DATA
GHABP	GLASGOW HEARIND AID BENEFIT PROFILE
HADS	HOSPITAL ANXIETY AND DISORDER SCALE
HMAC	HASH-BASED MESSAGE AUTHENTICATION CODE
HUI-3	HEALTH UTILITIES INDEX MARK 3
JSON	JAVASCRIPT OBJECT NOTATION
JWE	JSON WEB ENCRYPTION
JWS	JSON WEB SIGNATURE
JWT	JSON WEB TOKEN
LMM(s)	LINEAR MIXED MODEL(S)
MAC	MESSAGE AUTHENTICATION CODE
MOCA	MONTREAL COGNITIVE ASSESSMENT
PHAS	PUBLIC HEALTH ACTION SCENARIO
PHP	PUBLIC HEALTH POLICY
PHPDM(s)	PUBLIC HEALTH POLICY DECISION MODEL(S)
PSOS	PATIENT SUPPORT ORGANISATION'S SCENARIO
PTA	PURE TONE AUDIOMETRY
REST	REPRESENTATIONAL STATE TRANSFER
RSA	RIVEST–SHAMIR–ADLEMAN
SIN	SPEECH IN NOISE
SNR	SIGNAL-TO-NOISE RATIO
SPL	SOUND PRESSURE LEVEL(S)
TTS	TEMPORARY THRESHOLD SHIFT
WP5	WORK PACKAGE 5

Executive Summary

The present deliverable (D5.6) describes the functionalities of the Decision Support System (DSS) and Simulation Component within the EVOTION project. It outlines the results of Task 5.5 of Work Package (WP) 5 of EVOTION. This has involved (i) defining the role for the DSS to be used within EVOTION, (ii) developing a text-mining component to be used for enhancement and refining of the Public Health Policy Decision Models (PHPDMs), (iii) identifying a common set of criteria to be applied on the PHPDMs for selection and simulation purposes and (iv) development of the DSS. Work-Package 5 (WP5) of the EVOTION project has a number of specific aims, including the development of the DSS for supporting evidence-based policymaking. It also aims to enhance and co-ordinate analysis undertaken in the Big Data Analytics (BDA) ensuring integrated outputs into a suitable form to be incorporated within the DSS, and finally develop tools to enable the continued support of evidence-based hearing health policies beyond the EVOTION's lifecycle.

Based on the description of the scenarios, the functional requirements and the overall architecture of the EVOTION platform in previous deliverables, there was a common decision among EVOTION partners to deviate from the described course of action and provide a new role the DSS, a public-health policy driven one. This role is tied to the decision-making processes and is better aligned with the functionality and the characteristics of the Public Health Policy Decision Models (PHPDMs).

Evidence-based policymaking enables policy makers to make justified decisions in the complex reality of hearing health related interventions. It refers to the use of objective, scientifically based evidence in all stages of the policy making process. Two important pillars for evidence-based hearing health policy making are hearing health data and statistics and scientific knowledge that lead to an increase in awareness of concepts associated with evidence-based practice and patient-centered care, consistent with current research-to-practice dissemination pathways (Boisvert et al., 2017). This type of policymaking can be beneficial (e.g., helps to identify hearing aid usage related problems and select the most appropriate interventions) but also has its challenges (e.g. a lot of information at varying levels of detail is required to inform decisions). The DSS that has been developed within EVOTION aims to support public-health policy decision makers as well as other stakeholders in their evidence-based policymaking.

In addition to evidence-based policymaking, the EVOTION DSS is grounded in the health systems approach (De Savigny et al., 2009), promoted by World Health Organization (WHO). The systems approach aims to provide a way forward for operating more successfully and effectively in complex, real-world settings regarding hearing health and takes into account all 'components' in a system, which contribute to the decision-making process for the formulation of a public health policy. In EVOTION, the systems approach is being integrated in the DSS in two main ways:

- First, the text-mining elements which relate to the PHPDMs will be linked to policies in any or all of related data relationships if appropriate.
- Second, the comparison and simulation of models' instances will contribute to the added value of complementary actions included in a PHPDM and provide a better understanding and link to supporting actions.

1 Component Overview

The Decision Support System (hereinafter mentioned as DSS) is one of the key components inside the EVOTION platform. There is a trifold purpose underpinning the DSS functionality:

- The first purpose of the DSS is to provide a text-mining component that will strengthen existing links or identify missing connections among the parameters composing the Public Health Policy Decision Models (hereinafter mentioned as PHPDMs) as these were initially described in Deliverable D3.1 (Katrakazas et al., 2017).
- The second purpose is to provide a simulation component with an enhanced version of the aforementioned PHPDMs, complementing the Big Data Analytics (hereinafter mentioned as BDA) results. This approach will allow the creation of sub- and super-sets of model instances, depending on a public health policy maker's choice
- The third purpose of the DSS is to identify the most appropriate instance of each set of models, based on specific criteria, which are defined by the PHPDM Transformation Tool component. This functionality serves as a decision-making assistant to the public health policy maker.

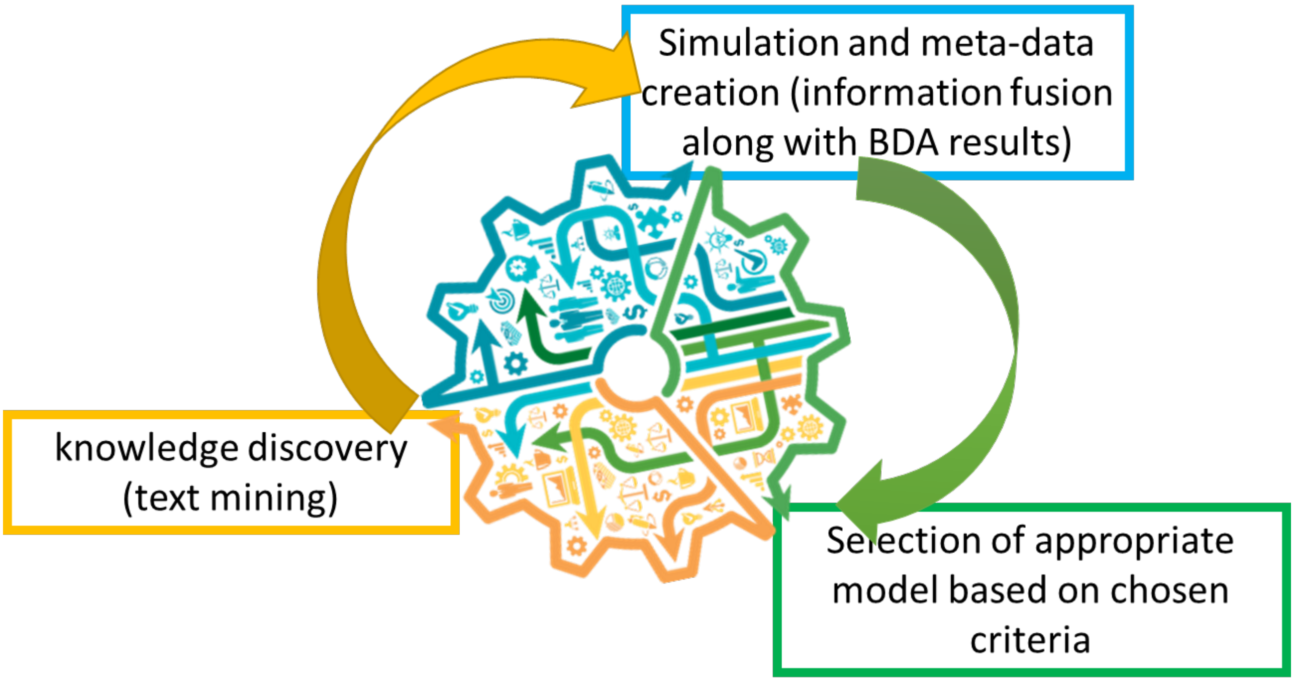

Figure 1 EVOTION DSS Purposes

1.1 DSS requirements

The list of requirements identified for the purposes of the EVOTION scenarios, were described in Deliverable D2.1 (Dimakopoulos et al., 2017). Out of those requirements, the ones underpinning directly or indirectly the principles under which the DSS should work are shown in following Table 1. Table 2 shows the interactions of the DSS with other components as those were described in Deliverable D2.2 (Ye et al., 2017).

Table 1 DSS Functional Requirements

Functional Requirement ID	Title	Priority of accomplishment	Related to Platform (P) or/and Mobile (M)
FR(PHAS)2	Discover factors of low HA usage	Must have	P
FR(PHAS)3	Identify relevant studies and provide a summary of them	Must have	P
FR(PHAS)4	Filter the relevant studies	Must have	P
FR(PHAS)5	Cluster the relevant studies	Should have	P
FR(CLIS)7	Provide a list of studies for inspection	Should have	P
FR(PHAS)11	Administrate (create, update, delete) analysis' outcomes	Must have	P
FR(PHAS)12	Notification when analysis is complete	Must have	P
FR(PHAS)13	Visualizations of the analysis' outcome	Must have	P
FR(PHAS)14	Suggest factors of analysis' outcome	Must have	P

Table 2 DSS Component Interactions

Scenario	Components to Interact With
SD – CLIS. 4	PHDPM Specification Tool
SD – PHA. 1	PHDPM Specification Tool
SD – PHA. 2	PHDPM Specification Tool
SD – PHA. 3	PHDPM Specification Tool
SD – PHA. 4	PHDPM Specification Tool
SD – PSOS. 7	Data Repository, Social Campaigning Tool

1.2 Structure of deliverable

The first (current) section provides background information about the EVOTION DSS and the list of requirements underpinning its principles. Section 2 introduces the DSS role along with its architecture approach. Section 3 introduces the key components of the DSS, those being the text mining (TM) and decision support component, along with their development features. Sections 4 and 5 provide an overview of the DSS pre- and post-model operations, including their design and development. Section 6 provides the software services developed for the DSS and the demonstrator developed for D5.6 purposes. Section 7 concludes the report, summarising the current situation and detailing the next steps.

2 Overview: Decision Support System and its Role in EVOTION

The current deliverable (D5.6) is the outcome of Task 5.5 Decision Support System. The initial description of the aforementioned task, as described in the Description of Action (DoA) was the following:

> *<u>T.5.5 Development of the EVOTION decision support system (Leader: ICCS, M9-M20)</u>: This task will focus on the development of the EVOTION's decision support system. The purpose of this system will be to aid clinicians (i.e., ENT doctors and audiologists) to make decisions about the adjustment of settings of HAs of specific patients. Such adjustments will be necessary in cases where automated and/or patient triggered adjustments executed by the HA adaptation engine cannot address the needs of the patients. Similarly to the HA adaptation engine, the DSS will take into account the hearing loss and wider profile of individual patients, the patterns of usage recorded for them, evidence about the difficulties that they have experienced whilst using HA in different contexts (e.g., when exposed to different noise levels, when performing different tasks), and established clinical guidelines regarding appropriate settings in different circumstances. In addition, it will take into account the history of adjustments performed by the HA adaptation engine (whether automated or patient triggered) in order to reason and identify adjustments with poor results for the specific patients and enable clinicians make decisions about the more challenging issues faced by them. DSS will also help clinicians identify and manage the longer term management of patients through decisions about auditory training, alternative treatments (e.g. use of HAs with different characteristics, cochlear implant interventions etc.), and management actions regarding cognitive challenges faced by the patients and/or prevention of cognitive deterioration. The EVOTION DSS won't be able to execute HA adjustments directly; it will have to execute them through EVOTION's HA adaptation engine.*

However, Task 4.3 in DoA indicates that there should be a connection between the DSS and the Public Health Policy Decision Making (PHPDM) Models Transformation Tool (marked in bold):

> *<u>T.4.3 Development of the PHPDM model transformation tool (Leader: CITY, M18-M30)</u> This task will focus on the development of a tool to enable the transformation of PHPDM models specified in the language developed in T.4.1 into a form that can be executed by the BDA component of the EVOTION platform. This will be necessary in order to automate the generation of the different types of evidence required by the PHPDM model.* ***The same tool will also generate decision-making rules for the decision support system of the EVOTION platform, which will be necessary for generating possible decisions from the model that can drive the overall decision-making process involving the decision makers identified by the model****.*

Therefore, and based on the description of the scenarios, the functional requirements and the overall architecture of the EVOTION platform in deliverables D2.1 (Dimakopoulos et al., 2017) and D2.2 (Ye et al., 2017), there was a common decision among EVOTION partners to deviate from the described course of action. Based on a common agreement and adapting to the changes dictated by the aforementioned submitted deliverables, ICCS in its capacity as Task's 5.5 Leader, has proceeded with describing and providing a new role for the DSS. This new role does not follow the initial description of task 5.5 that indicated the development of a clinical DSS, but a public-health policy driven role, tied to the decision-making processes described in Task 4.3. The following figure (Fig. 1) shows the twofold role of the DSS that is aligned with the functionality and the characteristics of the Public Health Policy Decision Models (PHPDMs):

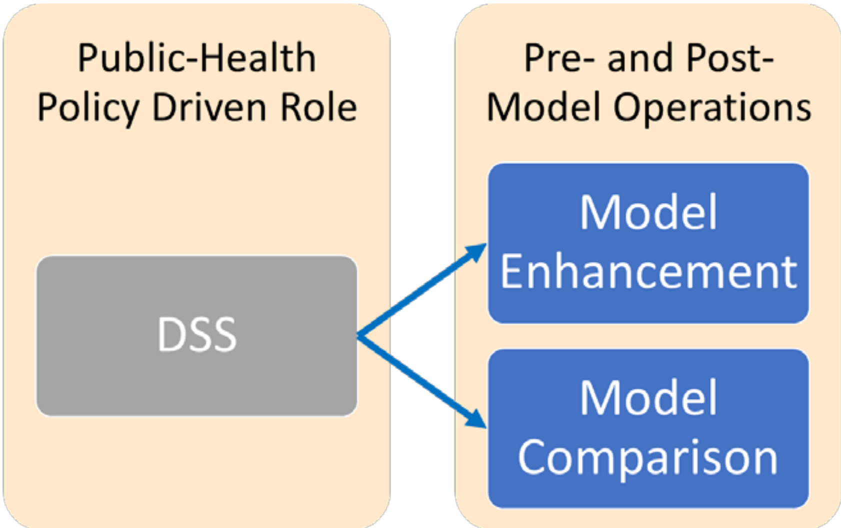

Figure 2 EVOTION DSS Role

This new role is better suited to assist public health policy makers in their decision-making, shifting its original focus from a clinical perspective to a public health policy one. Given the need to interact with the PHPDMs described in D3.1 (Katrakazas et al., 2017), the DSS has two operation modes, that are further described in Section 3:

1. Pre-Model Operation: Model Enhancement
2. Post-Model Operation: Model Comparison (including simulation elements)

Based on this role and adhering to the architecture described in Deliverable D2.2 (Ye et al., 2017), the DSS component's placement in the EVOTION platform is shown in Fig. 3:

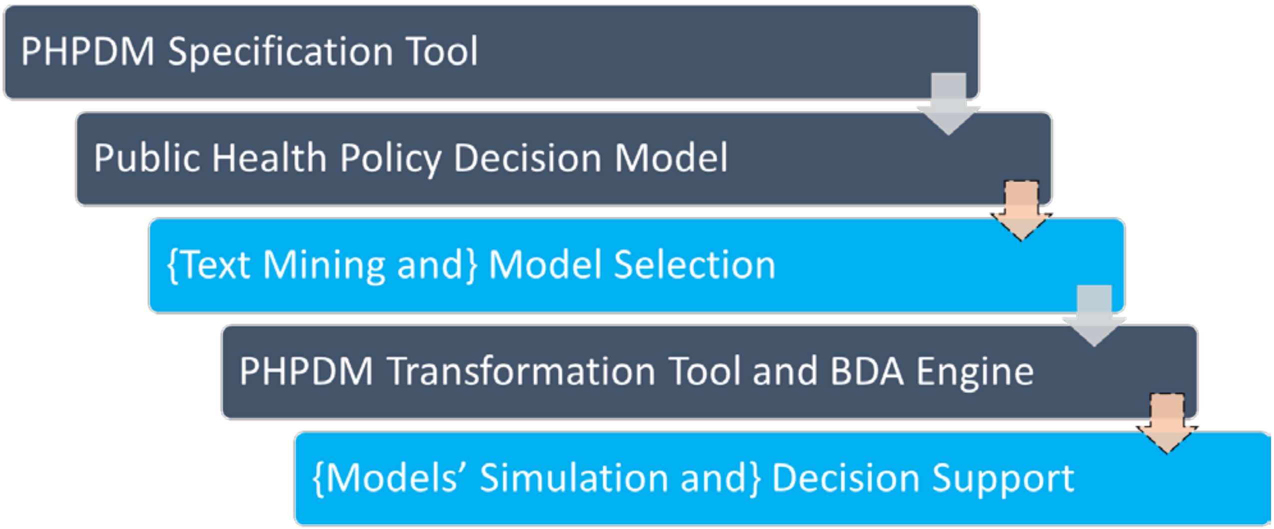

Figure 3 Positioning of DSS in the EVOTION platform

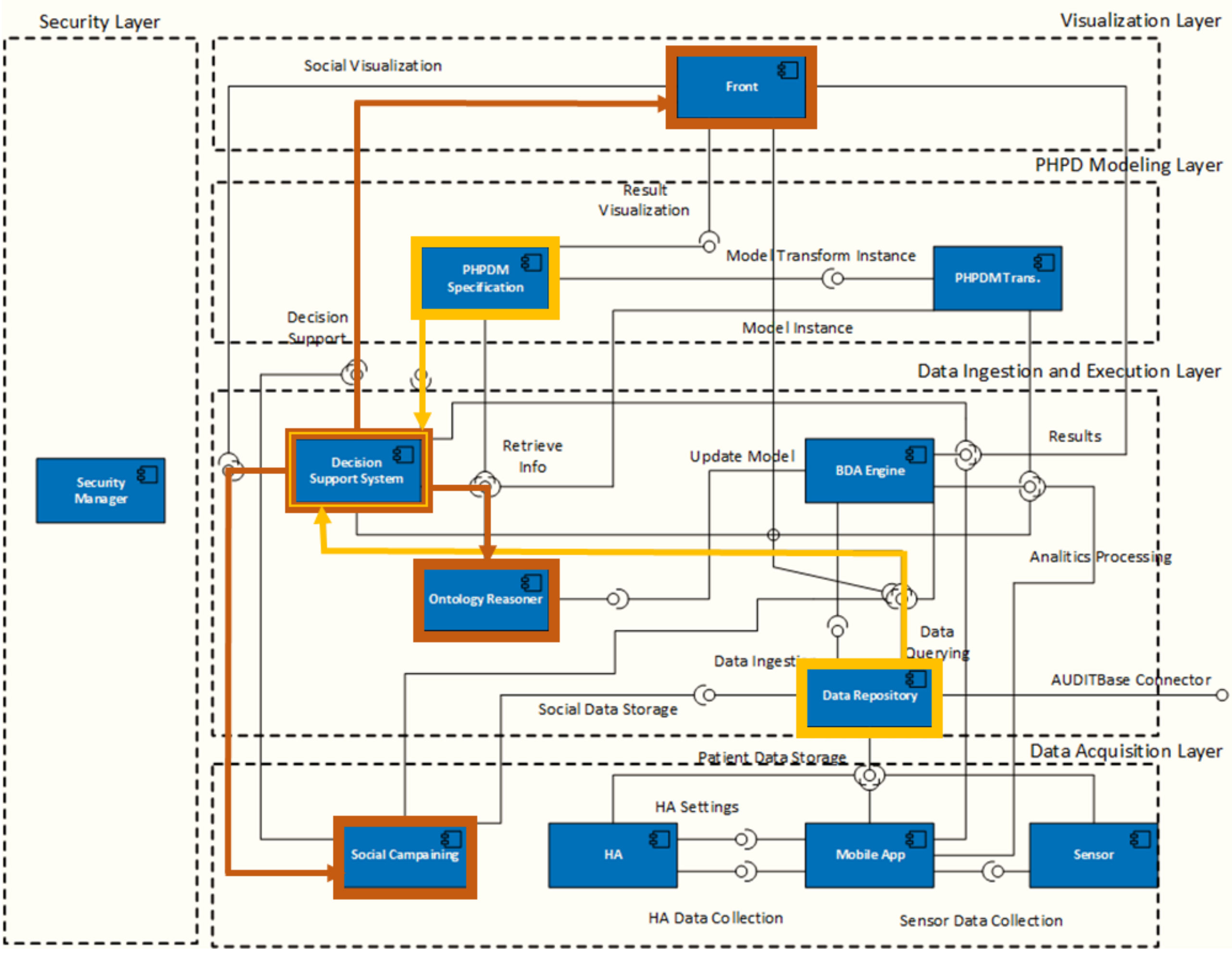

Figure 4 DSS connections in the EVOTION platform architecture

Fig.4 depicts the connections of the DSS component inside the EVOTION platform architecture. Light orange indicates DSS input connections, while dark orange indicates DSS output connections. More specifically:

1. The PHPDM Specification Tool sends a PHPDM instance to the DSS for the DSS to update it. This is an optional action to be selected by the PHP actor (pre-model operation)
2. The DSS sends the updated PHPDM to the Ontology Reasoner (pre-model operation), which in turn sends it to the BDA Engine.
3. The BDA Engine sends a notification alert to the DSS, described in Deliverable D5.5 (Anisetti et al., 2018), triggering the DSS to query the Data Repository. The Data Repository sends the different versions of the PHPDMs along with decision-making rules produced by the PHPDM Transformation Tool to the DSS. These rules will be applied to the different instances of the models, so that the DSS will decide which instance(s) satisfy the rules (post-model operation)
4. DSS sends the final model(s) to the Social Campaigning Tool in order for the latter to inform the public about policies generated by the PHPDM models. (post-model operation)
5. DSS also sends the outcomes of its functions to the Dashboard for visualization purposes.

2.1 Use of decision support systems in Public Health Policy Making

Apart from the structural and functional reasons presented in the previous section, there was a strategic need for shifting the DSS to a PHP-driven role. A DSS can be seen as a

tool to support the decision-making process in the public health policy area especially, if it uses readily available clinical and demographic features. This could permit a more rapid, evidence-based decision-making in public health. However, up until now, there has been limited use of such systems in public health policy making.
With the advent of big data paradigms in the last few years, there has been a rise in data science approaches, raising in parallel a higher demand for effective data-driven models that support decision-making at a strategic level. This motivates the need for defining novel data analytics and decision support approaches in a myriad of real-life scenarios and problems, with hearing-health related domains being no exception. Therefore, the present section serves also as a grounding framework to concentrate the most updated insight obtained from such tools (decision support models/frameworks/systems) in public health policy making and advance them in the EVOTION DSS.
Over the last five (5) years, attempts towards a PHP-DSS include:

1. a comprehensive framework to evaluate infectious disease mitigation strategies (Pizzi, 2013)
2. a case-based reasoning model for the support of decision-making in public health (Mera et al., 2015).
3. a DSS related to PHP decisions to improve health awareness and services by linking health effects data with levels and frequency of environmental exposure (Hudspeth and Budge, 2013).
4. a conceptual DSS proposed to outline potential policy decisions about a health technology, as well as a list of the criteria for making these decisions, aiming to link the information provided through a Health Technology Assessment report to those policies. (Yazdani and Jadidfard, 2016).

This short review of existing PHP-related DSS worldwide indicated an existing gap in evidence based policy making in hearing health, while the vast majority of information did not include a big-data analysis approach. Although a list of decision support systems related to tinnitus has been recently identified (Tarnowska et al., 2017), a connection with the public-health policy related area is not made. An analysis of user (public health policy makers and clinicians) needs together with the EVOTION common analysis methodology, led to the definition of design principles of the DSS. All these actions have led not only to the design of the DSS, but also to the development of the DSS. Fig. 5 illustrates the inter-relationship between several data management, analytics and decision support techniques and methods commonly adopted in the EVOTION framework.

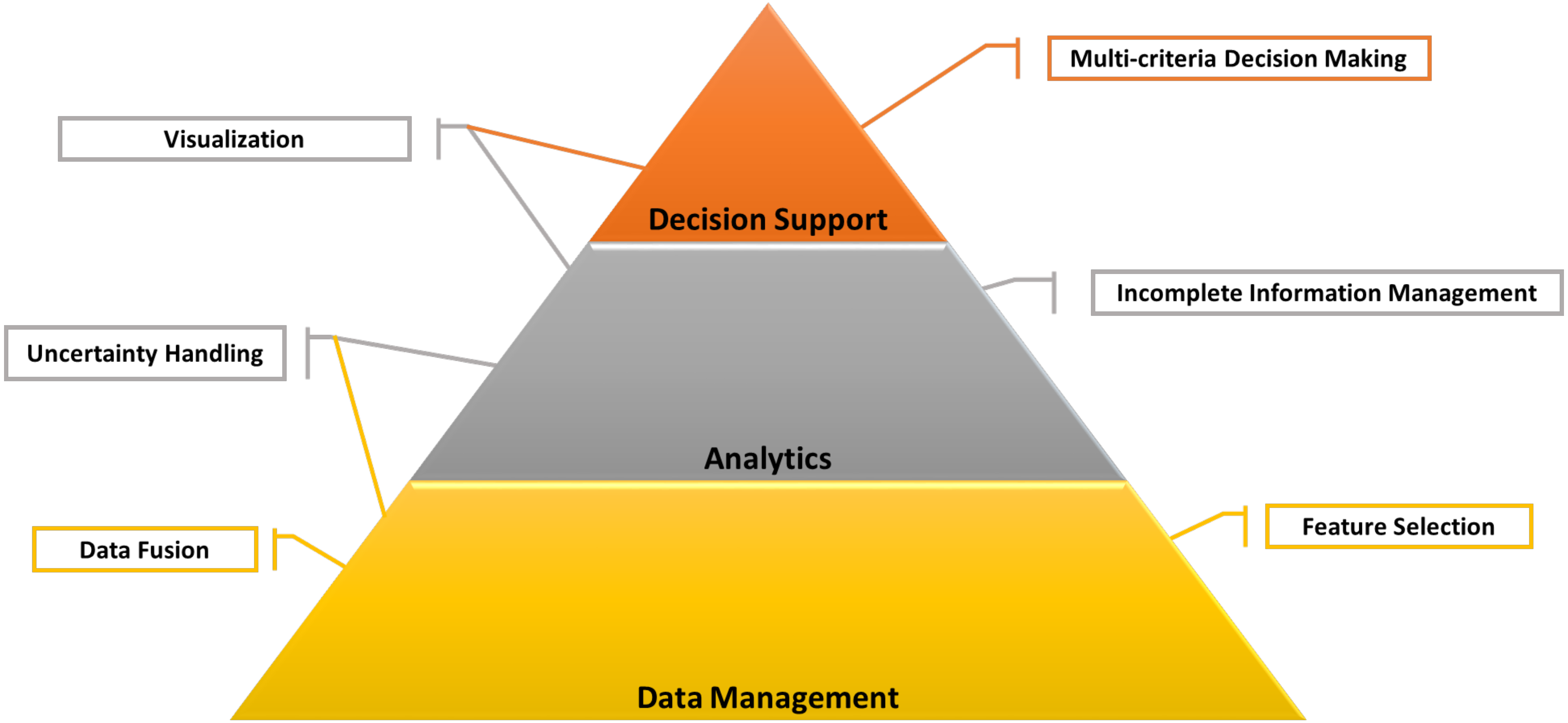

Figure 5 Inter-relationship between data management, analytics and decision support techniques in EVOTION

3 Design: Text-Mining and Decision Support Component

As there is no recent work for PHP modelling in the hearing health area, the EVOTION public health policy and clinical stakeholders who participated in the two WP3-related workshops have recognised that literature review may provide some indications as to where to look for the purposes of formulation of the PHPDMs. Moreover, the EVOTION BDA Engine can employ this knowledge to build an updated situation analysis, taking into consideration the EVOTION-monitored factors that were not mentioned in the literature.

As there is not an actual paradigm of policymaking employing big data in hearing health, the DSS may use multiple BDA computations on top of the text-mining analytics to indicate the possible decisions for the public health policy actor.

3.1 Review of existing Text-Mining Technologies and their application in EVOTION

There is a number of different text-mining techniques; however, the most commonly identified are the following:

1. Document Classification (text classification, document standardization),
2. Information Retrieval (keyword search/ querying and indexing)
3. Document Clustering (phrase clustering)
4. Natural Language Processing (spelling correction, lemmatization, grammatical parsing, and word sense disambiguation)
5. Information Extraction (relationship extraction / link analysis),
6. Web Mining (web link analysis)

Out of these techniques, the ones deemed useful for the EVOTION purposes are the Information Retrieval (IR) and Information Extraction (IE).

1. Information Retrieval

   Information Retrieval (IR) refers to a process of extracting relevant and associated patterns according to a given set of (key)words or (key)phrases. Since there is a close relationship between ext mining and information retrieval for textual data, application of IR in relevant databases (i.e. Pubmed https://www.ncbi.nlm.nih.gov/pubmed/) will attain results that are more significant and provide users (i.e. public health policy actors) with more relevant and appropriate information to be incorporated into the PHPDMs.

2. Information Extraction (IE)

   Information Extraction (IE) refers to a technique that extracts meaningful information from a large amount of text. Implementation of IE pinpoints the attributes and relation according to a specific domain. In EVOTION this process is used to extract specific attributes and/or entities from the document corpus and establish their relationship. Precision and recall processes are used to check and evaluate the relevance of results on the extracted data. In-depth and complete information about the relevant field for its relevant stakeholders is required to attain more relevant results (Talib et al., 2016).

Fig. 6 shows the Venn diagram of text-mining techniques adopted from (Talib et al., 2016) showing where the novelty of the Text-Mining Component of the EVOTION DSS lies: while IE and IR are seemingly mutually exclusive (disjoint) sets, EVOTION DSS acts as the intersection set among these groups, for the PHPDM processes to take place.

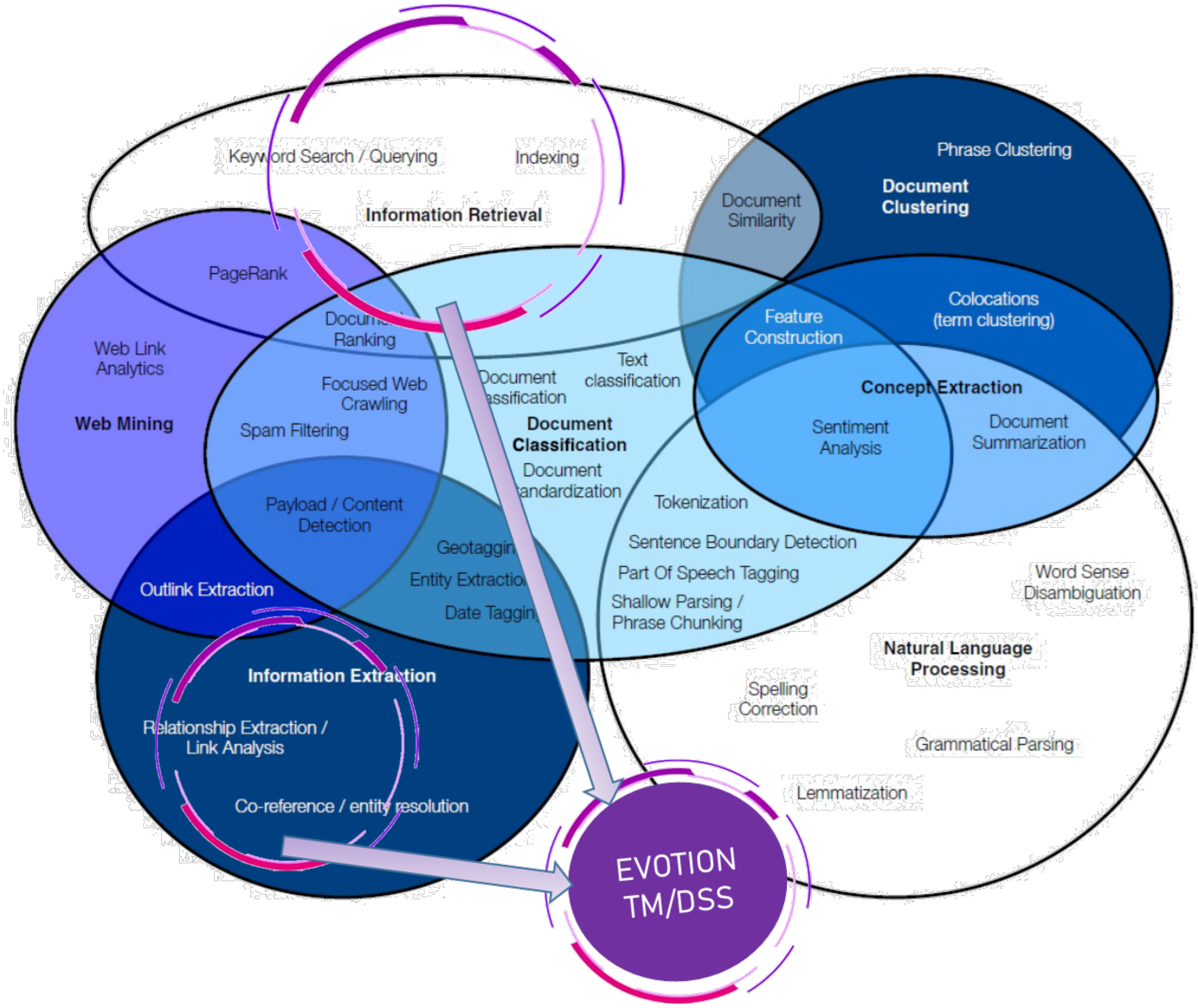

Figure 6 EVOTION TM functionalities on top of TM techniques (Talib et al., 2016)

3.2 Text-Mining and Decision Support Component Development

Both the Text-Mining and the Decision-Support Components were developed using the R language. R (https://www.r-project.org/) is considered to be one of the most popular open source programming languages for data science, and its packages are useful in understanding and extracting insights from the text via a text mining processes. The following packages were used (a brief description of each package, along with its source link, is accompanying them):

- RISmed
  - Description: The RISmed package is used to download content from the United States of America (USA) National Center for Biotechnology Information

    - (NCBI) databases. RISmed includes a set of tools to extract bibliographic content from the NCBI databases, including PubMed.
    - Source: https://cran.r-project.org/web/packages/RISmed/
- SnowballC
    - Description: The SnowballC package provides an R interface to the C libstemmer library that implements Porter's word stemming algorithm for collapsing words to a common root to aid comparison of vocabulary.
    - Source: https://cran.r-project.org/web/packages/SnowballC/index.html
- tm
    - Description: The tm package is a framework for text-mining applications
    - Source: https://cran.r-project.org/web/packages/tm/index.html
- Wordcloud
    - Description: The wordcloud package provides a commonly used plot to visualize a set of documents in a succinct way/
    - Source: https://cran.r-project.org/web/packages/wordcloud/index.html
- Jsonlite
    - Description: The jsonlite package is a fast JSON parser and generator optimized for statistical data and the web. The package offers flexible, robust, high performance tools for working with JSON in R and is particularly powerful for building pipelines and interacting with a web API.
    - Source: https://cran.r-project.org/web/packages/jsonlite/index.html
- Dendextend
    - Description: The dendextend package offers a set of functions for extending 'dendrogram' objects in R.
    - Source: https://cran.r-project.org/web/packages/dendextend/
- nlme
    - Description: The nlme package is used to fit and compare linear and nonlinear mixed-effects models.
    - Source: https://cran.r-project.org/web/packages/nlme/index.html
- lme4
    - Description: The lme4 packages is used to fit linear and generalized linear mixed-effects models.
    - Source: https://cran.r-project.org/web/packages/lme4/index.html

4 Design: DSS Pre-Model Operations

4.1 Text-Mining Operations

Section 2.4 presented just an example of a pre-model operation of the Text-Mining Component. However, there are additional operations prior to any PHPDMs' finalisation that can be performed. At this point, we need to clarify that any pre-model operations are to be performed by the Text-Mining Component, as these operations serve as an enhancement feature for any PHPDM, based on existing evidence, found in current literature. The full list of pre-model operations of the DSS is hereby presented:

Table 3 List of Pre-Model Operations

#	Operation	Description
1	Download relevant abstracts from Pubmed	Based on user's input(s) (i.e. keyword-s, starting and ending year, stopwords) the DSS downloads the relevant abstracts from Pubmed
2	Create a corpus	Based on user's inputs (see 1), a corpus is created for text-mining analysis
3	Save corpus	Corpus created is saved in a .csv file
4	Update stopword list	Users may update the stopword list
5	Perform text-mining on corpus	Users perform text-mining on the corpus
6	See maximum number of reports papers per year	Users may see the maximum number of papers per year
7	See Summaries of data	Users may see the Summaries (Abstracts) of the selected downloaded reports
8	See Pubmed IDs of data	Users may see the Pubmed identification numbers (IDs) of the downloaded reports
9	Show frequency of n words	Users see the frequency of n words in the corpus based on text-mining function
10	Show word frequencies per year	Users see the word frequencies per year
11	Show most frequent terms	Users see the most frequent terms in a barplot format
12	Show most frequent terms (2)	Users see the most frequent terms in a wordcloud format
13	Show most frequent terms (3)	Users see the most frequent terms in a hierarchical clustering format
14	Save results in a .pdf file	Users save the results of their search in a .pdf file
15	Save results in a .json file	Users save the results of their search in a .json file

4.1.1 Description of text-mining operations 1 and 3

When exploring large corpora (such as the PubMed database), analysts are confronted with the problem of selecting relevant documents for qualitative investigation and further quantitative analysis. The corpus under investigation in the EVOTION DSS is of dynamic nature and comprises of several hundreds of thousands of articles, depending on the keywords entered by the user. The absolute majority of them might be considered as irrelevant for the research question posed.

Moreover, when investigating a new topic area or seeking an update on a known research area, searching an online collection of abstracts of journal articles is often the first approach. The strategy used to search abstracts databases is central to how successful a finding will be. A search query that is too broad will pick up many abstracts that might be deemed useless, while one too specific query might be too limiting for an expansive search. This may require the use of Boolean search constructs and techniques such as delimiting the search by restricting it to specific fields, for example, searching only author names, or only article titles. As far the EVOTION project is concerned, the main focus of the Text-Mining Component is to identify new connections among concept areas, therefore a full-text approach (which would also require a taxonomy and document clustering approach) is not recommended for such a case.

Thus, the first of the three tasks introduced in an analysis workflow is concerned with the objective to reduce a large data set to a smaller, manageable set of potentially relevant documents. This can be related clearly to an ad hoc task of IR comparable to search applications such as library systems or web search engines.

In standard scenario of ad hoc IR, users generally have a specific, well-defined information need around specific topics or concrete (named) entities. This information need can be described with a small set of concrete key terms for querying a collection. Furthermore, the information need can be satisfied with a relatively small number of documents to be retrieved.

To meet these special requirements, the following procedure of IR using *contextualized dictionaries* is described. In this approach, a query is not based on single terms compiled by the content analyst. Instead, the query is automatically built from a set V of reference terms coming from EVOTION PHPDMs. Compared to the problem of determining concrete key terms for a query, it is rather easy for analysts to manually compile a collection of 'paradigmatic' terms which reflect topics or thematic areas matching their research objective. Retrieval for a set of documents $D' \subseteq D$ with such a reference collection V is then performed in two steps:

1. Extract a substantial set of key terms from the reference collection V, called dictionary (see Section 4.2). Terms in the dictionary are used to reflect the different parameters measured in EVOTION in importance for describing an analysis objective.
2. Extract term co-occurrence statistics from the reference collection V.

4.1.2 Description of TM operation 2

Text-mining on a large collection of documents is usually a complex process, thus it is critical to have a data structure for the text which facilitates further analysis of the documents. Analyzing text computationally requires the transformation of documents, i.e. sequences of character strings, into numerical data suitable for quantifying evaluation, statistical inference or modeling. Usually, for such a transformation documents need to be separated into single lexical units, which then are counted.

The most common way to represent the documents is as a bag of words, which considers the number of occurrences of each term (word/phrase) but ignores the order. This representation leads to a vector representation that can be analyzed with dimension reduction algorithms from machine learning and statistics, e.g. Latent Semantic Indexing, Probabilistic Latent Semantic Indexing and topic models (the last one is used in EVOTION).

Topic modelling is one of the most popular probabilistic clustering algorithms, the main idea of which is to create a probabilistic generative model for the corpus of text documents. In topic models, topic models, documents are a mixture of topics, where a topic is a probability

distribution. In a topic model usually topics with undesired content can be identified. In contrast to other keyword extraction methods which neglect interdependence of terms, the topic model approach allows to exclude such unwanted semantic clusters. Before calculating term weights, one simply has to identify those topics not representing meaningful structures and to remove them from the set.
In order to be able to define the importance of a word in a document, documents are represented as vectors and a numerical importance is assigned to each word. The three most used models based on this idea are vector space models (used in EVOTION), probabilistic models and inference network models.

4.1.3 Description of text-mining operations 4 and 5

Depending on the application, the analysis unit for counts may be altered from documents to paragraphs or single sentences to narrow down certain contexts, or document sets for aggregating information on higher discursive levels. After definition of the analysis unit and its corresponding data separation, e.g. detecting sentence boundaries in documents, single lexical units, also known as *tokens*, need to be identified. This process, called 'tokenization', separates all distinct word forms present in the entire text corpus. Such distinct word forms are called *types*. Again, counts of types for every analysis unit can be encoded and stored in a vector—collections in a Document-Term Matrix (DTM) respectively.
The way in which text is tokenized mainly influences posterior analysis steps as it defines the atomic representatives of semantics. Tokens might be single terms, punctuation marks, multi-word units, or concatenations of *n* tokens, so called *n*-grams encoding different aspects of semantics numerically. Computer linguistics comprises of a variety of procedures to preprocess textual data before encoding it in a DTM. After initial encoding, the DTM may be further preprocessed mathematically, e.g. to weight terms by their contribution to document meaning. Linguistic and mathematical preprocessing of the DTM prepare subsequent TM analysis. The following list briefly introduces the most common preprocessing steps used in the EVOTION TM component:

- <u>Tokenizatio</u>n: Separation of text into single tokens can be achieved in many languages simply by separating at white space characters. However, this base line approach misses separation of punctuation marks from single terms or does not cover recognition of Multi Word Units (MWUs).
- <u>Cleaning</u>: For specific use cases, not all identified types of lexical units contribute to the desired level of meaning. For example, stop words such as articles or pronouns often do not cover relevant aspects of meaning in a 'distant reading' perspective. The same can be valid for punctuation marks or numbers in the text. If useful, such types of lexical units can be omitted to reduce the amount of data and concentrate on the most meaningful language aspects for subsequent analysis.
- <u>Unification</u>: Lexical units occur in different ways of spelling and syntactical forms. Variants of the same noun may occur in singular, plural or different cases, verbs may be inflected. Unification procedures reduce such forms to a single basic form, to treat occurrences of variances in the data as an identical event for all further applications. Common forms of unification are reduction of characters to lowercase, stemming and lemmatization. For stemming, word stems of terms are guessed by cutting suffixes from tokens according to a language specific rule set (used in EVOTION).

These procedures of preprocessing distinctively shape the set of types to be counted to prepare a DTM by identifying, transforming and filtering lexical units with respect to text knowledge. There is no ideal or correct configuration of such a preprocessing chain.

Instead, each application demands its own parameter settings to yield optimal results. Often it is necessary to experiment with different parameters for preprocessing before deciding which results fit best to study requirements, and that was the approach followed in the EVOTION DSS, as it can also be seen in the example in Section 4.2.

4.1.4 Description of text-mining operations 6-13

The lexicometric applications of the EVOTION TM component are hereby presented:

- Frequency analysis: In this application, observations of events, e.g. specific terms or concepts occurring in documents, are counted and counts are compared across dimensions, e.g. time. Observing term frequencies in a longitudinal view over several decades may reveal peaks and dips in term usage, and corresponding concepts. Events for observation can be defined in distinguishable ways, e.g. as raw term frequencies or as document frequencies where multiple occurrences of one term in the same document are counted only once.
- Information Extraction: This application strives for the identification of names, terms or concepts in a document. Usually, it is realized by probabilistic sequence classification determining the most probable category for any token in a sentence. For EVOTION, IE is useful to identify terms or concepts associated with any other information identified in a text, e.g. any other information occurring in a contextual sequence.
- Co-occurrence analysis: or co-occurrence analysis, joint occurrence of events in a well-defined context unit is observed and evaluated by a statistical test. For any word type it reveals a ranked list of other words which co-occur with it more often than expected under the assumption of independence, e.g. in a sentence or as its left/right neighbor or a hierarchical clustering approach (which is used in the EVOTION TM component). In accordance with structuralist linguistic theory, this reveals semantic fields of syntagmatically related terms. Comparing and ranking such semantic fields by similarity further may reveal paradigmatically related terms, i.e. concepts occurring in similar contexts.

4.1.5 Description of text-mining operations 14-15

Results of the aforementioned operations are saved in .pdf format and .json format, for user friendly and data-exchange friendly format for syncing the data between two web applications.

5 Design: DSS Post-Model Operations

The post-model operations of the DSS are the ones related to the decision support that the DSS can offer to public health policy experts. Evidence-informed decision-making involves integrating the best available research evidence into the decision-making process. Additional factors, such as patients' health issues and local context, community and political preferences, imperatives and actions, and public health resources, also play an important role and may influence decisions. It is important to note that any public-health policy related model is not considered as static but rather dynamic. Therefore, in any given public health situation, the different factors may be weighted differently from other health situations in making a final decision. Examples of some of the evidence that can impact decision making are summarized in the table below.

Table 4 Evidence-informed Decision Making and EVOTION capabilities

Factor(s)	*Sources of evidence to take into account*
Research evidence (E)	• The most relevant, high-quality qualitative or quantitative evidence available • Research findings from EVOTION clinical partners
Health issues in a local context (E)	• Health status reports to determine the magnitude of the health issue in a local setting • Significance and importance of the issue in comparison to other health concerns
Community and political preferences and actions (NE)	• Needs and interests of community members • Support or opposition from the public/government officials • Current political climate (local, regional, provincial, federal) • Current organizational/corporate climate
Public health resources (~E)	• Financial resources • Cost, cost-effectiveness and cost-benefit analysis in comparison to other interventions • Human resources (personnel/staffing, administrative support, support from management, training in the Public Health Approach) • Materials (workspace, supplies)

E: covered by EVOTION, NE: not covered by EVOTION, ~E: partially covered by EVOTION

In order to promote the awareness and use of the EVOTION platform to assist public health professionals in their efforts to incorporate research evidence in practice, programme, and policy decisions, the EVOTION DSS builds up on the results incorporated into the PHDPMs after their analysis from the BDA engine (see Fig. 5). The PHPDMs are described in the high level language described in D4.1 (Prasinos et al., 2017), which aims towards the specification of evidence based health policy decision making models based on big data analytics. This language enables the specification of:

- the overall goal and the specific objectives that public policy needs to address
- the range of possible actions (interventions) through which the goals/objectives of the policy can be achieved
- the evidence that needs to be gathered to make informed and plausible decisions about the actions (interventions)
- the processes for analysing and establishing the validity of this evidence
- the stakeholders who will consider the evidence and decide which actions (interventions) should be undertaken
- the criteria that should be used to make decisions on the basis of the evidence.

Therefore, one of the key objectives of the DSS is to provide the public-health policy actors a user-friendly, web-based, interactive Decision Support Tool which will enable policy-makers and stakeholders to select, simulate, compare and implement the most appropriate strategies, measures and cost-effective (if applicable) approaches for hearing health related issues.

The PHPDM execution enables automated transformations onto scripts of the BDA engine and every execution will be stored as instances of the model, allowing full traceability for decision-making and auditability in policymaking. Based on these principles, the DSS is set to enable comparisons of executions upon different datasets that compose the PHPDMs. Given the nature of these models, we first present the theoretical background behind these principles.

5.1 Background Theory

Given the elements of the language presented in the previous section, a PHPDM can be loosely described by the following relation:

$$PHPDM \sim \{Goals(Objectives) = Actions(Stakeholders(Evidence, Criteria))\} \quad (1)$$

From the previous relation, we can see that a $Goal$, described by its $Objectives$, can be achieved through $Actions$, which are affected by the $Stakeholders$, who in turn base their decision on the $Evidence$ (including their analysis) and the $Criteria$ parameters. Therefore, the decision-support tool aimed for the stakeholders, which is the second DSS's objective, is primarily focused on the parametrical set of $(Evidence, Criteria)$.
As the nature of PHPDMs is a complex one, they can be considered as mixed (or multilevel) models, which is also clear from (1) as the final result is multi-level based. Mixed model data have a more complex, multilevel and hierarchical structure, something that can be also identified in the EVOTION Data Repository (Basdekis et al., 2017). Observations between data levels or data clusters are independent, but observations within each cluster are dependent because they belong to the same subpopulation.

An advantage of using mixed models is the ability to combine the data by introducing multilevel random effects. Mixed models are described as nonlinear statistical models, due mainly to the presence of variance parameters, and thus they require special theoretical treatment. The mixed models approach can be used for a number of purposes, however we here present the ones serving the EVOTION DSS purposes, which are:

- to model complex clustered or longitudinal data
- to model data with multiple sources of variation
- to cope with parameter multidimensionality

The two most common ways to deal with such hierarchical data are the following:

- Aggregation: although aggregate data analysis yields consistent and effect estimates and standard errors, it does not really take advantage of all the EVOTION data, because the selected data would be simply averaged, giving a small amount of data points.
- Data analysis from one unit at a time: Although this approach might work in the EVOTION case, we have many instances of the models, and each one does not take advantage of the information in data from other cases. This can also make the results "noisy" in that the estimates from each model are not based on a significant amount of data.

As we need a decision-support tool to be able to *(a) simulate and (b) select a* model, the Linear Mixed-Effects Models, or Linear Mixed Models (LMMs) approach is considered most appropriate for the EVOTION case. LMMs is an important class of statistical models that can be used to analyze correlated data, including clustered observations, repeated measurements, longitudinal measurements, and multivariate observations. Such data compose the EVOTION dataspace, thus making the LMMs approach from a DSS-perspective a perfect match. Moreover, as the EVOTION data consist of measurements taken multiple times from the same sample sets or samples belonging to different groups (e.g. patients from different hospitals), the mixed effects is appropriate for modelling the parameters of the EVOTION dataspace.

The analysis of continuous, hierarchical data using LMMs, allows taking into account the correlation of observations contained in a dataset and allows public-health policy makers to partition overall variation of the chosen dependent variables into components corresponding to different levels of data hierarchy. PHPDMs are examples of subject-specific models, because they include subject-specific coefficients. This makes LMMs ideal to explore and understand important effects that could affect a stakeholder's decision regarding the evidence they see.

5.2 Linear Mixed Models Approach to Model Selection

In a broad sense, LMMs are used to quantify the relationship between a dependent variable and a set of covariates with the use of a linear function depending on a small number of regression parameters. Formulation and methods for LMMs are hereby described for data with a single level of grouping, with N groups indexed by $i = 1, \ldots, N$, each containing n_i observations. Of course, this can be extended to multilevel grouped data. The following sections briefly describe the key elements that build up to the model selection purposes.

5.2.1 Model Specification

For hierarchical data with a single level of grouping, a classical LMM at a given level of grouping factor is formulated as follows:

$$\boldsymbol{y}_i = \boldsymbol{X}_i\boldsymbol{\beta} + \boldsymbol{Z}_i\boldsymbol{b}_i + \varepsilon_i \tag{2}$$

where $\boldsymbol{y}_i, \boldsymbol{X}_i, \boldsymbol{\beta}, \boldsymbol{\varepsilon}_i$ are the vector of continuous responses, the design matrix and the vector of residual errors for group i, specified in:

$$\boldsymbol{y}_i \equiv \begin{pmatrix} y_{i1} \\ \cdots \\ y_{in} \end{pmatrix}, \boldsymbol{\varepsilon}_i \equiv \begin{pmatrix} \varepsilon_{i1} \\ \cdots \\ \varepsilon_{in} \end{pmatrix} \tag{3}$$

$$\boldsymbol{X}_i \equiv \ (\boldsymbol{x}_i{}^{(1)}, \dots, \boldsymbol{x}_i{}^{(p)}) \tag{4}$$

and $\boldsymbol{Z}_i, \boldsymbol{b}_i$ are the matrix of covariates and the corresponding vector of random effects:

$$\boldsymbol{Z}_i \equiv \ (\boldsymbol{z}_i{}^{(1)}, \dots, \boldsymbol{z}_i{}^{(q)}) \tag{5}$$

$$\boldsymbol{b}_i \equiv \begin{pmatrix} b_{i1} \\ \cdots \\ b_{iq} \end{pmatrix} \tag{6}$$

Similar to the design matrix $\boldsymbol{X}_i$ the matrix $\boldsymbol{Z}_i$ contains known values of q covariates, with corresponding unobservable effects $\boldsymbol{b}_i$. Moreover, the residual errors $\boldsymbol{\varepsilon}_i$ for the same group are independent of the random effects $\boldsymbol{b}_i$. This particular assumption plays the key role in distinguishing a classical LMM from an extended LMM. In addition, we assume that vectors of random effects and residual errors for different groups are independent of each other.
In addition to the fixed-effects parameters $\boldsymbol{\beta}$ for the covariates used in constructing the design matrix $\boldsymbol{X}_i$, model (1) includes two random components: the within-group residual errors $\boldsymbol{\varepsilon}_i$ and the random effects $\boldsymbol{b}_i$ for the covariates included in the matrix $\boldsymbol{Z}_i$. The presence of fixed and random effects of known variables gives rise to the name of the model.

5.2.2 Model Diagnostics

After fitting an LMM, and before making any inferences based upon it, it is important to check whether the model assumptions are met. The two main distributional assumptions for model (1) pertain to the normality of the random effects $\boldsymbol{b}_i$and of the residual errors $\boldsymbol{\varepsilon_i}$. Evaluation of the influence of individual observations on the model fit may also be of importance, Additionally, it might be of interest to check whether the fit of the model is sensitive to the inclusion or exclusion of certain observations. This process is called influence diagnostics.

5.2.3 Influence Diagnostics

The basic tool to investigate the influence of a given observation on the estimates of $\boldsymbol{\beta}$, $\boldsymbol{\theta}$, and σ^2 is the likelihood displacement.

$$LD_i \equiv 2[l_{Full}(\widehat{\Theta}; y) - l_{Full}(\widehat{\Theta_{(-\iota)}}; y)] \tag{7}$$

where $\hat{\Theta} \equiv \left(\widehat{\boldsymbol{\beta}}', \widehat{\boldsymbol{\theta}}', \widehat{\boldsymbol{\sigma}}^2\right)'$ is the Maximum-Likelihood (ML) estimate of Θ obtained by fitting the classical Linear Model to all data, while $\widehat{\Theta_{(-\iota)}} \equiv \left(\widehat{\boldsymbol{\beta}_{(-\iota)}}', \boldsymbol{\theta}_{(-\boldsymbol{\iota})}', \widehat{\boldsymbol{\sigma}}_{(-\iota)}{}^2\right)'$ is the ML estimate obtained by fitting the model to the data with the i-th observation excluded. The log-likelihood is expressed as follows:

$$l_{Full}(\boldsymbol{\beta}, \boldsymbol{\sigma}^2, \boldsymbol{\theta}) \equiv -\frac{N}{2}\log(\boldsymbol{\sigma}^2) - \frac{1}{2}\sum_{i=1}^{N}\log[\det(\boldsymbol{V}_i)] - \frac{1}{2\sigma^2}\sum_{i=1}^{N}(\boldsymbol{y}_i - \boldsymbol{X}_i\boldsymbol{\beta})'\boldsymbol{V}_i{}^{-1}(\boldsymbol{y}_i - \boldsymbol{X}_i\boldsymbol{\beta})] \quad (8)$$

with

$$\boldsymbol{V}_i(\boldsymbol{\theta};\ \boldsymbol{v}_i) = Var(\boldsymbol{y}_i)/\sigma^2 \quad (9)$$

where $Var(\boldsymbol{y}_i)$ is the variance-covariance matrix of $\boldsymbol{y}_i$.

5.2.4 Model Selection

Selection tools are pretty similar to those used for the Linear Models for correlated data, therefore the following test will be briefly described:

- Statistical Significance Tests for the Fixed Effects
- Tests for Variance-Covariance Parameters
- Confidence Intervals Construction for Model Parameters

5.2.4.1 *Hypotheses-Testing for Fixed-Effects*

Hypotheses about the parameters $\boldsymbol{\beta}$ are tested using the F-test, given by (4.36). The issue related to the computation of the degrees of freedom for the approximation of the distribution of the F-statistic by a central F distribution applies here. In the context of more complex models, such as the ones in EVOTION, a need may arise to discriminate between non-nested models, which differ both in the variance-covariance and the mean structures. In such a situation, the use of *information criteria* is a possible solution.

The use of such criteria can be motivated by considering the procedure of a likelihood-ratio test:

$$T_L \equiv -2[l(\widehat{\theta_o}; y) - l(\widehat{\theta_A}; y)] \quad (10)$$

Denoted by l_A and l_0, the values of a log-likelihood function are computed by using the estimates obtained under the alternative and the null hypothesis, respectively. In the likelihood-ratio test, the null hypothesis is rejected if:

$$l_A - l_0 > f(p_A) - f(p_0) \quad (11)$$

where p_A and p_0 are the number of unrestricted parameters in the models defined by the alternative and null hypotheses, respectively, and $f\ (\cdot)$ is a suitable function. The likelihood-rate test can be viewed as a comparison of a suitably "corrected" log-likelihood function for two nested models. This idea can be extended to the comparison of non-nested models. The main idea behind the criteria is to compare models based on their maximized log-likelihood value, while penalizing for the number of parameters. The most popular proposal is defined by using:

$$f(p) = p \tag{12}$$

leading to the so-called Akaike's information criterion (AIC). The model with the largest AIC is deemed best. However, in R the criteria are defined by using the negative of the differences, and in this case, the model with the smallest criterion value is deemed best. AIC aims to find the best approximating model to the true one, and selects the model that seems to best fit the data. Strictly speaking though, this is not a formal statistical testing approach. In this respect, it is also worth mentioning that the use of the log-restricted- likelihood based criteria for LMMs with different mean structures is also not advocated (Gałecki and Burzykowski, 2013).

5.2.4.2 *Hypotheses-Testing for Variance-Covariance Parameters*

This issue is related to the approach based on the information criteria. The approach is used when the hypothesis about $\boldsymbol{\theta}$ cannot be expressed in the way that it would lead to alternative and null models. In this case, we can apply information criteria, like AIC to select the model that seems to best fit the data. However, in that case, it has been suggested that none of the information criteria is optimal to select LMMs, and that more work is still needed to understand the role that information criteria play in the selection of LMMs. Irrespective of the approach selected, before conducting any statistical significance tests, the fit of the chosen final model should be formally checked using the residual diagnostic methods (Gałecki and Burzykowski, 2013).

5.2.4.3 *Confidence Intervals for Parameters*

Confidence intervals for the individual components of the parameter vector $\boldsymbol{\beta}$ can be constructed based on the t-distribution, used as an approximate distribution for the t-test statistic. On the other hand, confidence intervals for the parameters $\boldsymbol{\theta}_{\boldsymbol{R}}$, related to the matrix $\boldsymbol{R}_i$, and for σ can be obtained in the same way as for the case of LMs for correlated data: via a likelihood-ratio test or use of information criteria (e.g. AIC).

After fitting an LMM, confidence intervals for the transformed parameters can be constructed using the normal approximation to the distribution of the ML estimators. The confidence intervals can then be back-transformed to yield the corresponding intervals for variances (or standard deviations) and correlations (Gałecki and Burzykowski, 2013).

6 Security and Privacy

JSON Web Token (JWT) is a compact, URL-safe means of representing claims to be transferred between two parties. The claims in a JWT are encoded as a JSON object that is used as the payload of a JSON Web Signature (JWS) structure or as the plaintext of a JSON Web Encryption (JWE) structure, enabling the claims to be digitally signed or integrity protected with a Message Authentication Code (MAC) and/or encrypted. JWT defines a compact and self-contained way for securely transmitting information between parties as a JSON object. This information can be verified and trusted because it is digitally signed. JWTs can be signed using a secret, with the HMAC (hash-based message authentication code) algorithm or a public/private key pair using RSA (Rivest–Shamir–Adleman) or ECDSA (Elliptic Curve Digital Signature Algorithm).

6.1 JWT Authentication

JWT is the missing standardization for using tokens to authenticate on the web in general, not only for REST services. Currently, it is in draft status as RFC 7519 (https://tools.ietf.org/html/rfc7519). It is robust and can carry a lot of information, but is still simple to use even though its size is relatively small. Like any other token, JWT can be used to pass the identity of authenticated users between an identity provider and a service provider (which are not necessarily the same systems). It can also carry all the user's claim, such as authorization data, so the service provider does not need to go into the database or external systems to verify user roles and permissions for each request; that data is extracted from the token. Fig. 7 shows the JWT security schema.

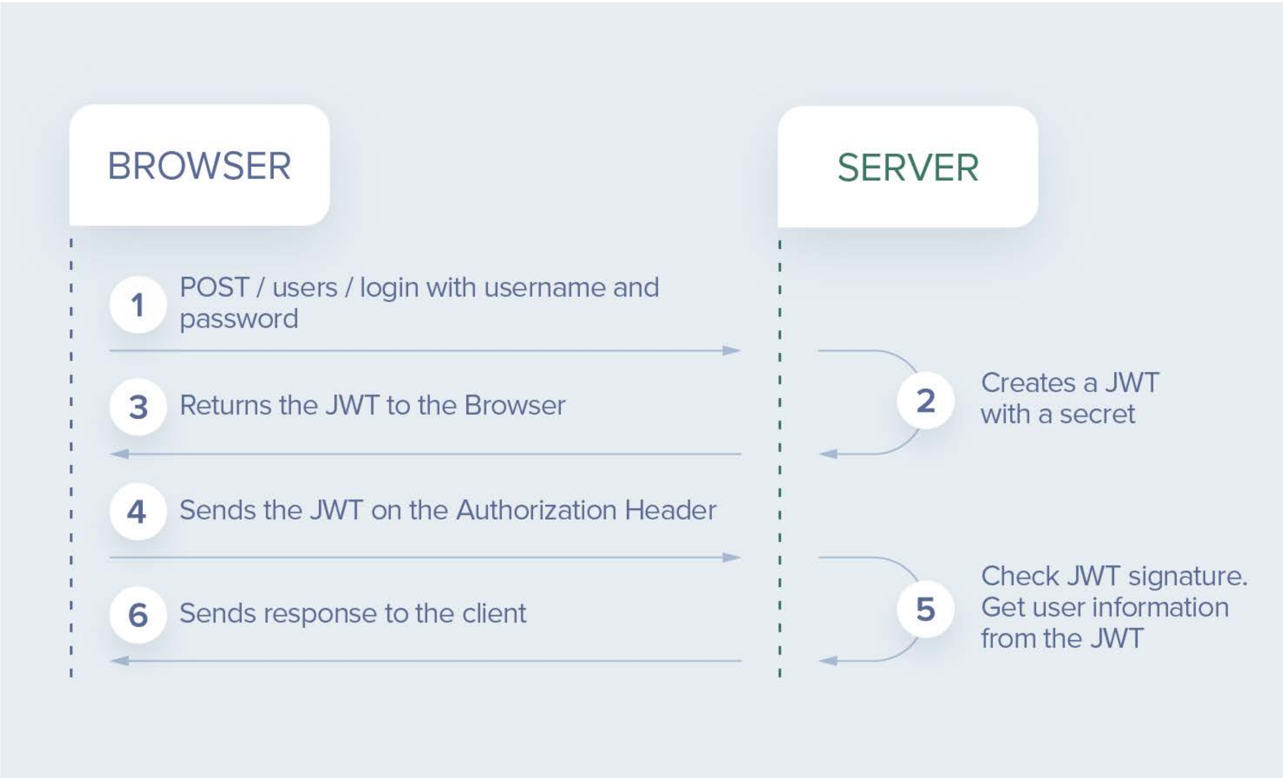

Figure 7 JWT Security Schema

- Clients log in by sending their credentials to the identity provider.
- The identity provider verifies the credentials. If everything is correct, it retrieves the user data and generates a JWT containing the user details and permissions that will be used to access the services. It also sets the expiration on the JWT (which might be unlimited).
- Identity provider signs, and if needed, encrypts the JWT and sends it to the client as a response to the initial request with credentials.
- Client stores the JWT for a limited or unlimited amount of time, depending on the expiration set by the identity provider.
- Client sends the stored JWT in an Authorization header for every request to the service provider.
- For each request, the service provider takes the JWT from the Authorization header and decrypts it. If needed, it validates the signature, and if everything is correct, it extracts the user data and permissions. Based on these data solely, and without looking up further details in the database or via contacting the identity provider, it can accept or deny the client request. The only requirement is that the identity and service providers have an agreement on encryption so that service can verify the signature or even decrypt which identity was encrypted.

This flow allows for great flexibility while still keeping things secure and easy to develop. By using this approach, it is easy to add new server nodes to the service provider cluster, initializing them with only the ability to verify the signature and decrypt the tokens by providing them a shared secret key. No session replication, database synchronization or inter-node communication is required.

6.2 REST Security Implementation

For the EVOTION DSS REST services to work as expected, we need a slightly different authorization approach. Instead of triggering the authentication process by redirecting to a login page when a client requests a secured resource, the REST server authenticates all requests using the data available in the request itself (the JWT token in this case). If such an authentication fails, there is no redirection; the REST API simply sends an HTTP code 401 (Unauthorized) response and then clients will send refresh-tokens to the server. If these tokens are valid, the server will generate a new pair of token/refresh-token, so that it makes a call again with a valid token. Otherwise, the client will log out and log in once again.

6.3 Sensitive Data Encryption

User login credentials are protected via the BCrypt algorithm. Bcrypt is an adaptive hash function based on the Blowfish symmetric block cipher cryptographic algorithm and introduces a work factor (also known as security factor), which allows to determine how expensive a hash function will be. This work factor value determines how slow the hash function will be, which means that different work factor will generate different hash values in different time span, which makes it extremely resistant to brute force attacks.

7 Implementation

Having described the purpose and envisioned functionalities of the DSS, we built the DSS application on multiple microservices. The communication between each microservice is designed in a Representational State Transfer- (REST)ful manner, to improve design consistency and maintainability.

The architecture is detailed below:

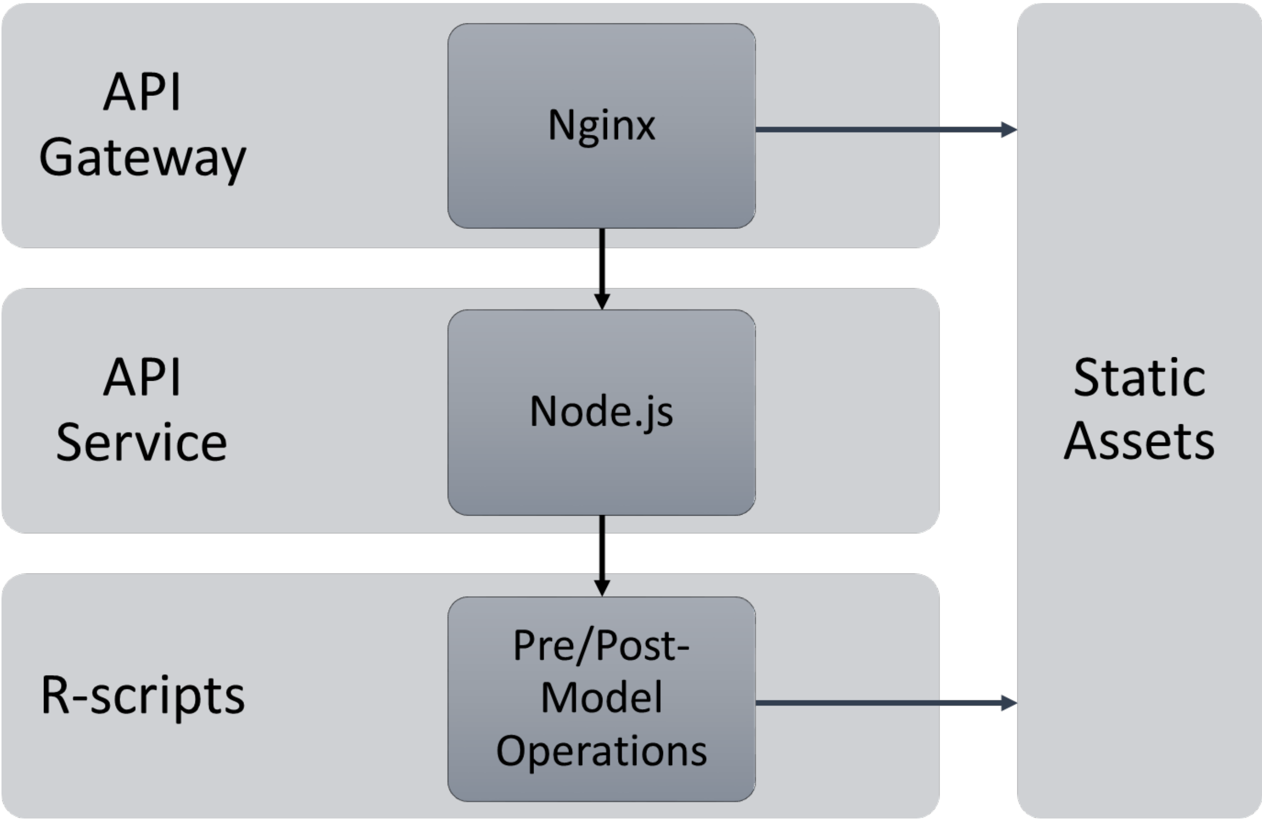

Figure 8 Architecture of DSS Software Services

7.1 Application Programming Interface Gateway

The aim was to create a single access point for calls to the DSS. To this end, a simple Nginx server was designed to handle all incoming load. The service has also been tasked with serving static application files and images. The Nginx service is also set to implement communication encryption. The reason for opting out for this additional nginx layer was to reduce the load on the node.js (Source: https://nodejs.org/en/, an open-source, cross-platform JavaScript run-time environment that executes JavaScript code server-side) Application Programming Interface (API) service.

7.2 Application Programming Interface Services

The main service is written in node.js to handle and authenticate user requests, using JWTs. The responsibilities include using the sequelized (http://docs.sequelizejs.com) Object-Relational mapping package and relaying client requests to the corresponding services.

7.3 Application service

The application front-end is developed using the ReactJS framework. It is to be bundled along in the app folder, only to be built from source by a node docker image and linked to the Nginx service as a static file.

7.4 R-scripts

Nginx-gateway servers either static files coming from static assets (public access) or proxy-passing to node.jst, which accepts the parameters to be used in the R-scripts, one for pre and post models operations. Node.js generates static files to nginx's public folder.

Initial request comes to nginx and from there it 'chooses' where to go.

7.5 Communications Interfaces

Endpoints between services are to be determined in the next iteration upon completion of elements connecting to the DSS (i.e Frontend Dashboard in M30, PHPDM Transformation and Specification Tools, Ontology Reasoner in M24).

7.6 Mock-ups

Prior to the process of designing and developing of the DSS, the first step is to create a set of website mock-ups to lay out the look and feel of the dashboard. These mock-ups are simple images to show what the website will look like. The mock-ups are just flat images that cannot be interacted with, but look like a screenshot of a website page. These mock-ups were used as a way to communicate design ideas back and forth with the EVOTION partners (clinical and public health policy actors) and also as a "blueprint" to develop the website once a common agreement is reached and the design is complete.
The following mock-ups for the DSS Dashboard were the initial attempt for the DSS development (Fig. 9-12) designed with the Balsamiq Mockups v3 application (source: https://balsamiq.com/products/)

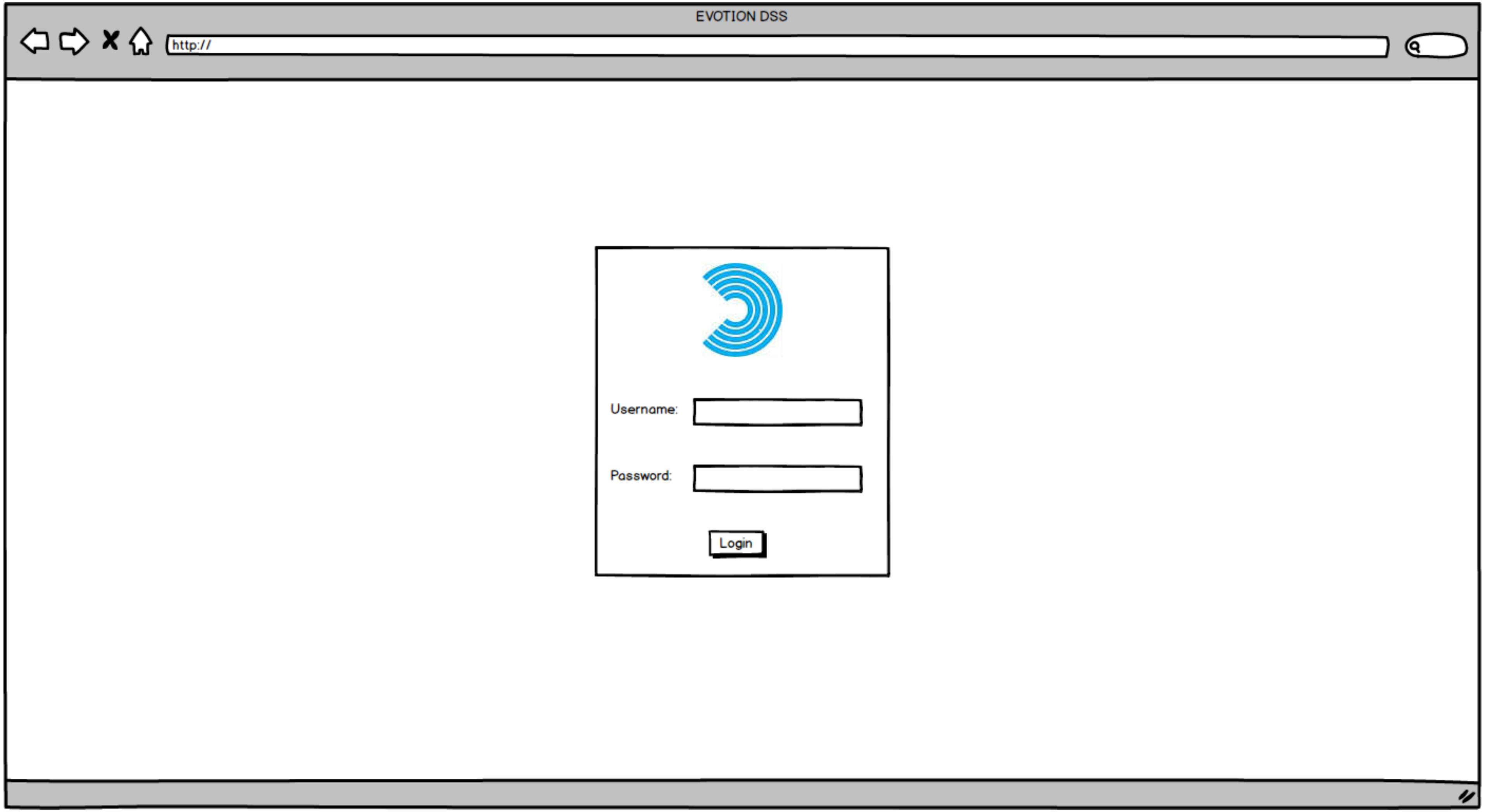

Figure 9 Mock-up for DSS Login Page

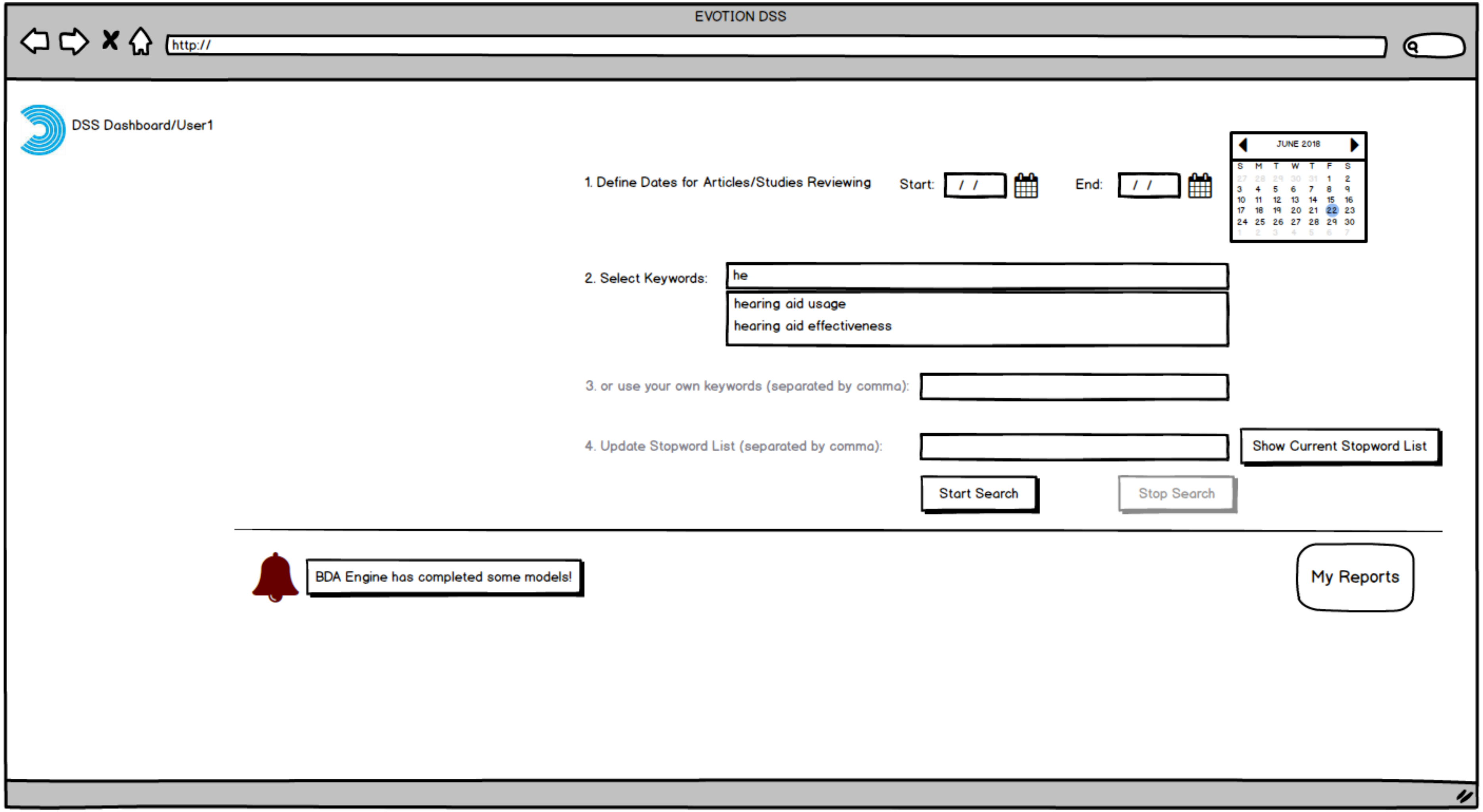

Figure 10 Mock-up for DSS User's Dashboard

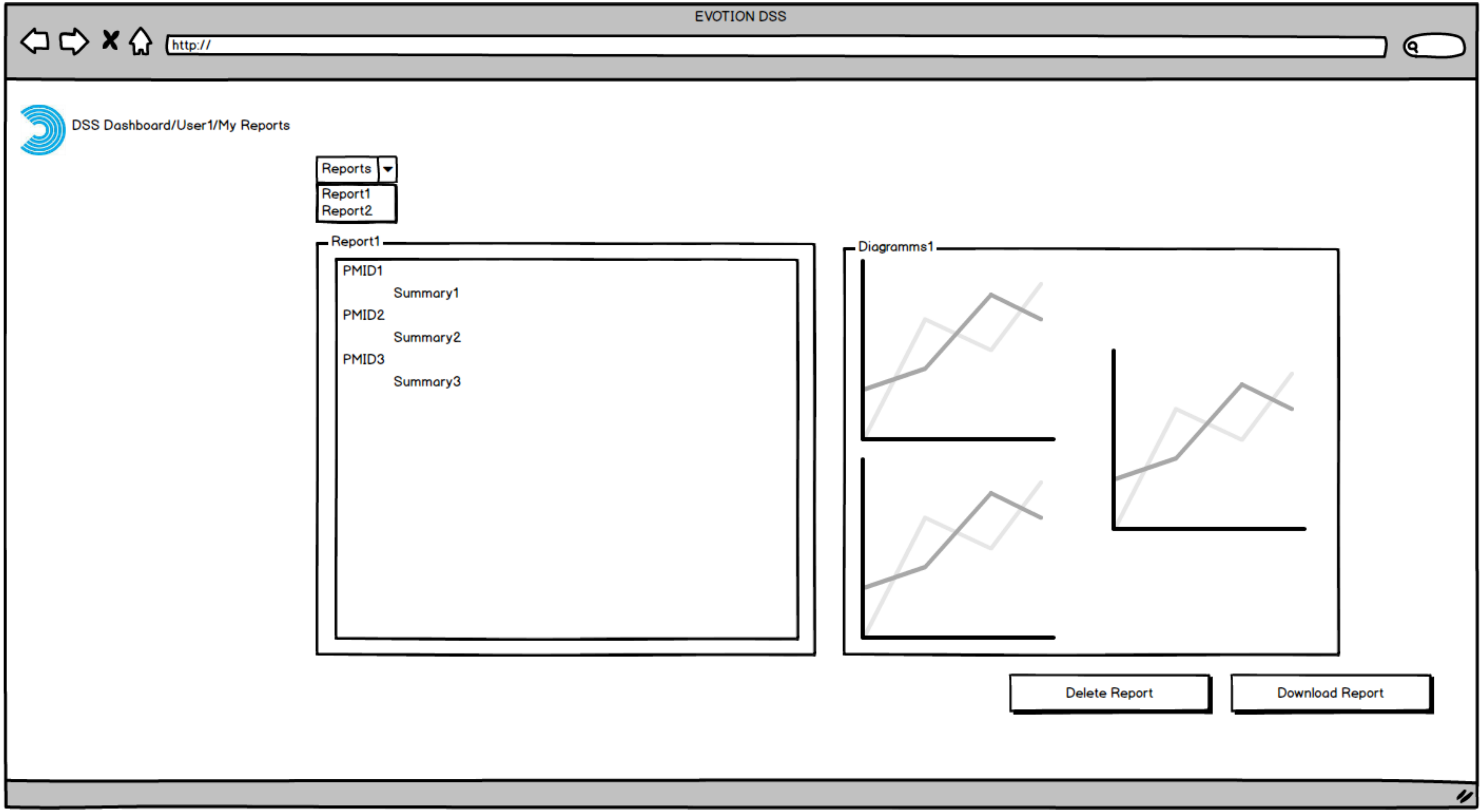

Figure 11 Mock-up for DSS Text-Mining Reports Page

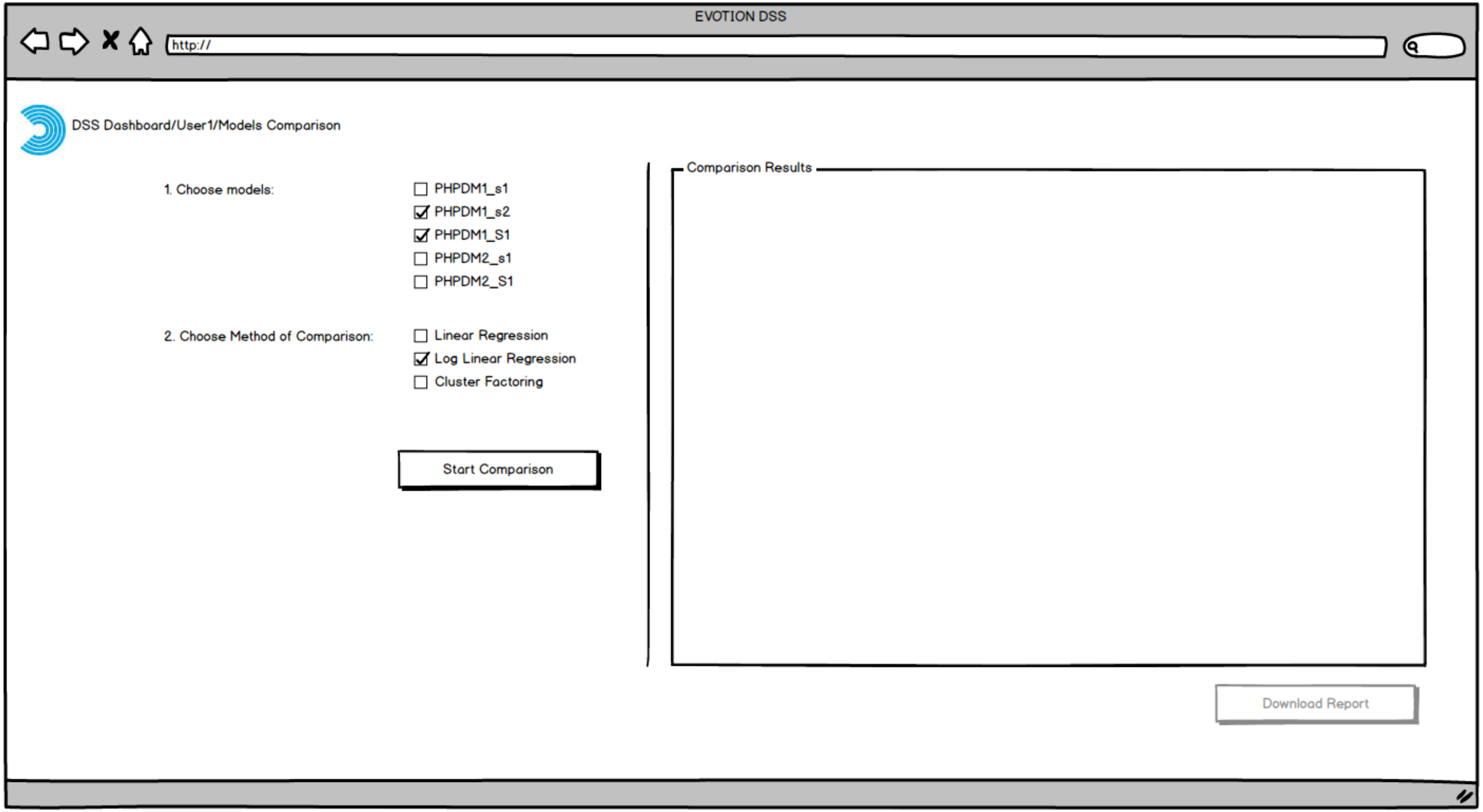

Figure 12 Mock-up for DSS Models Page

7.7 Actual Dashboard Screenshots

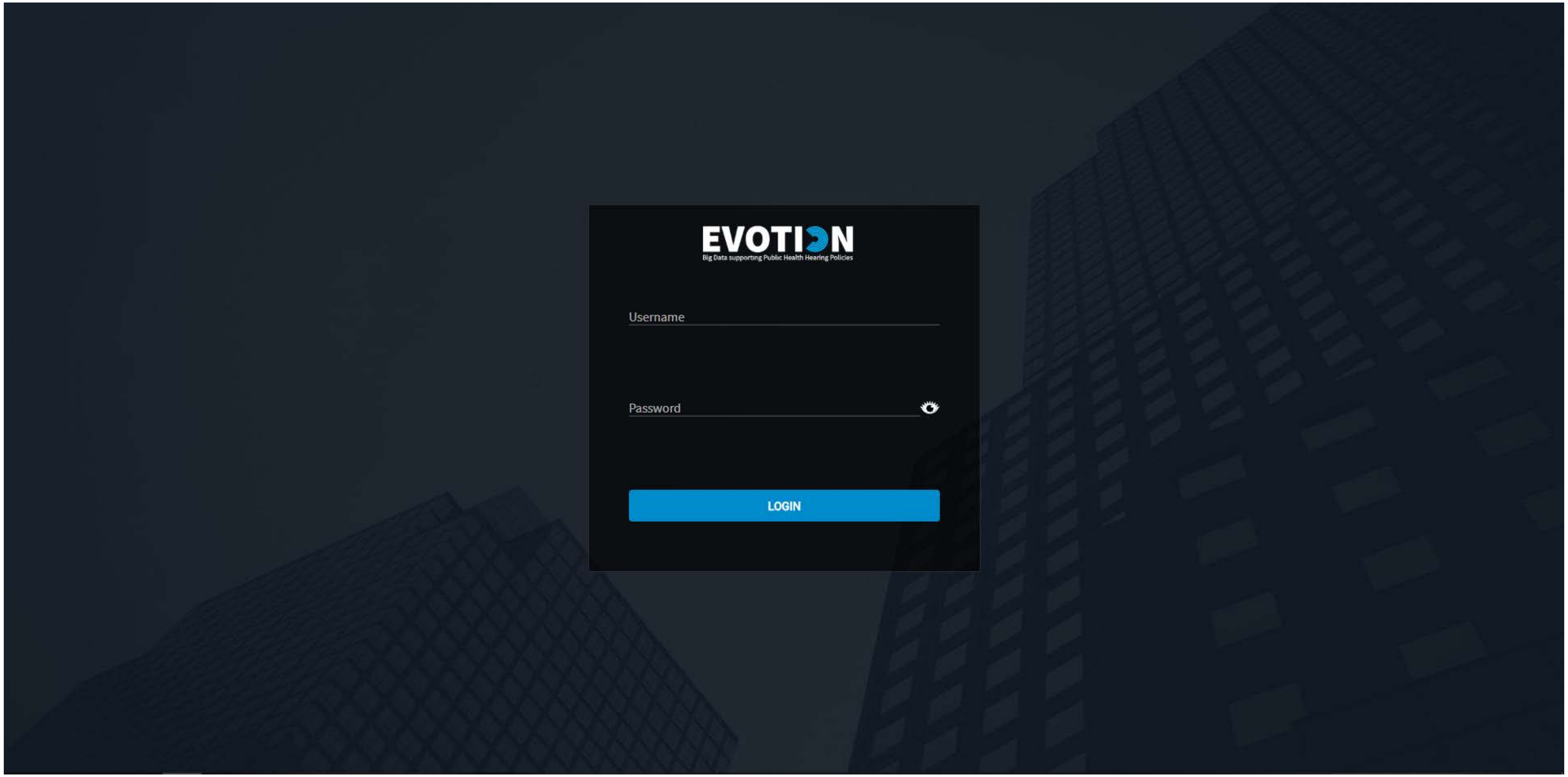

Figure 13 EVOTION DSS Login Page

Figure 14 Text-Mining Starting Page

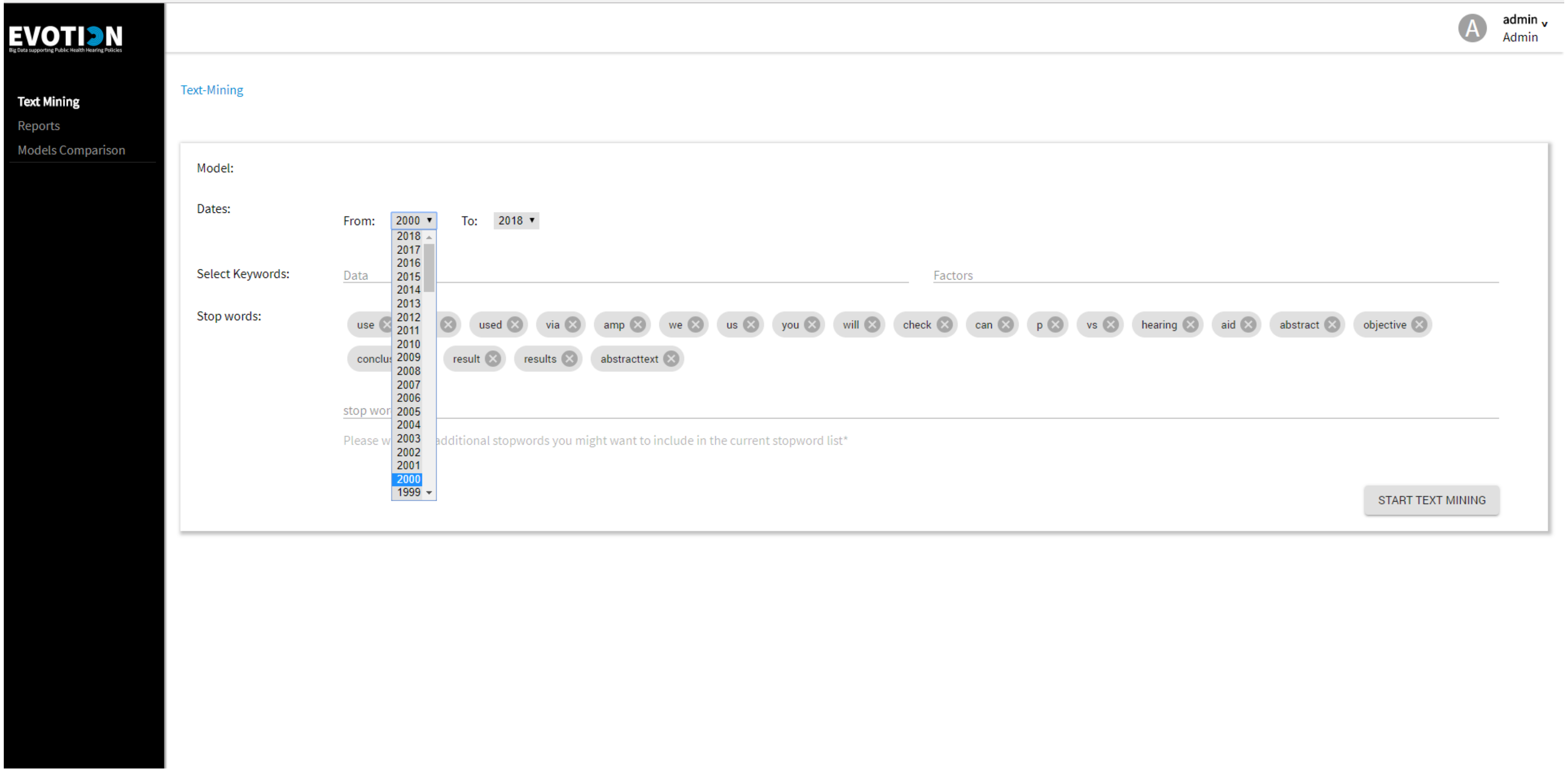

Figure 15 Text-Mining Date Selection

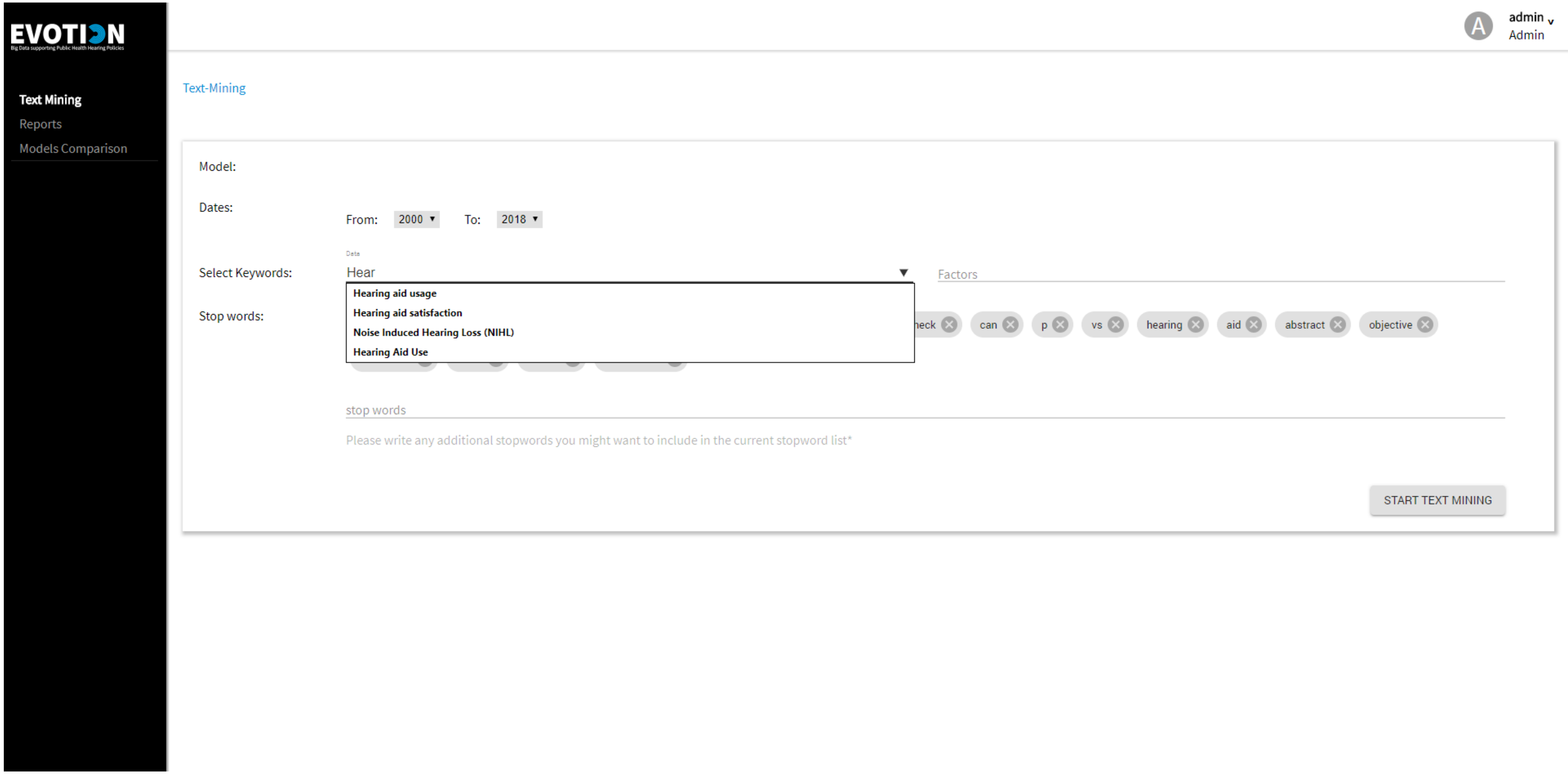

Figure 16 Text-Mining Data Selection

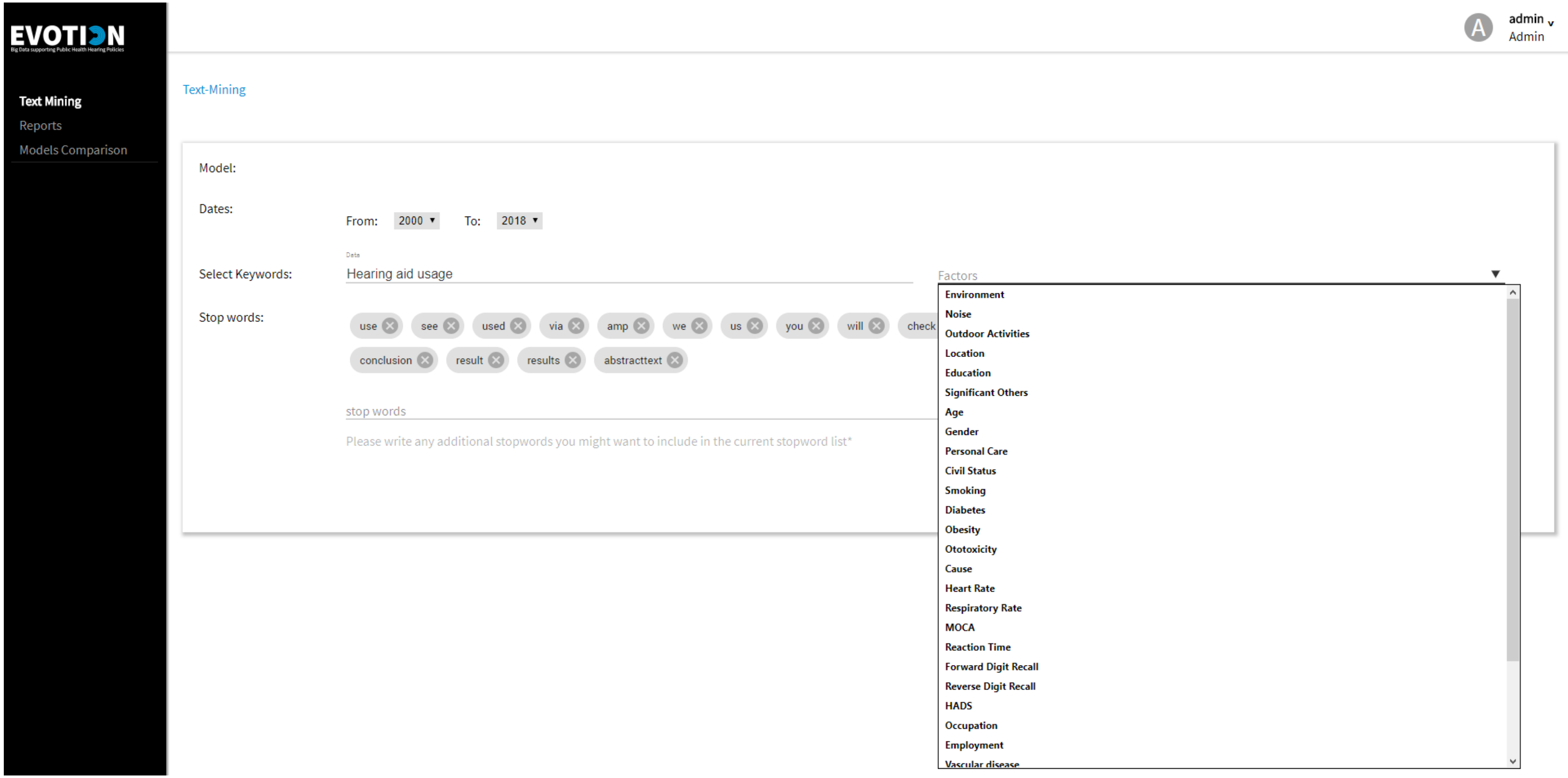

Figure 17 Text-Mining Factor Selection

Figure 18 Text-Mining Stopword Update and Automated Model Identification (upper left corner)

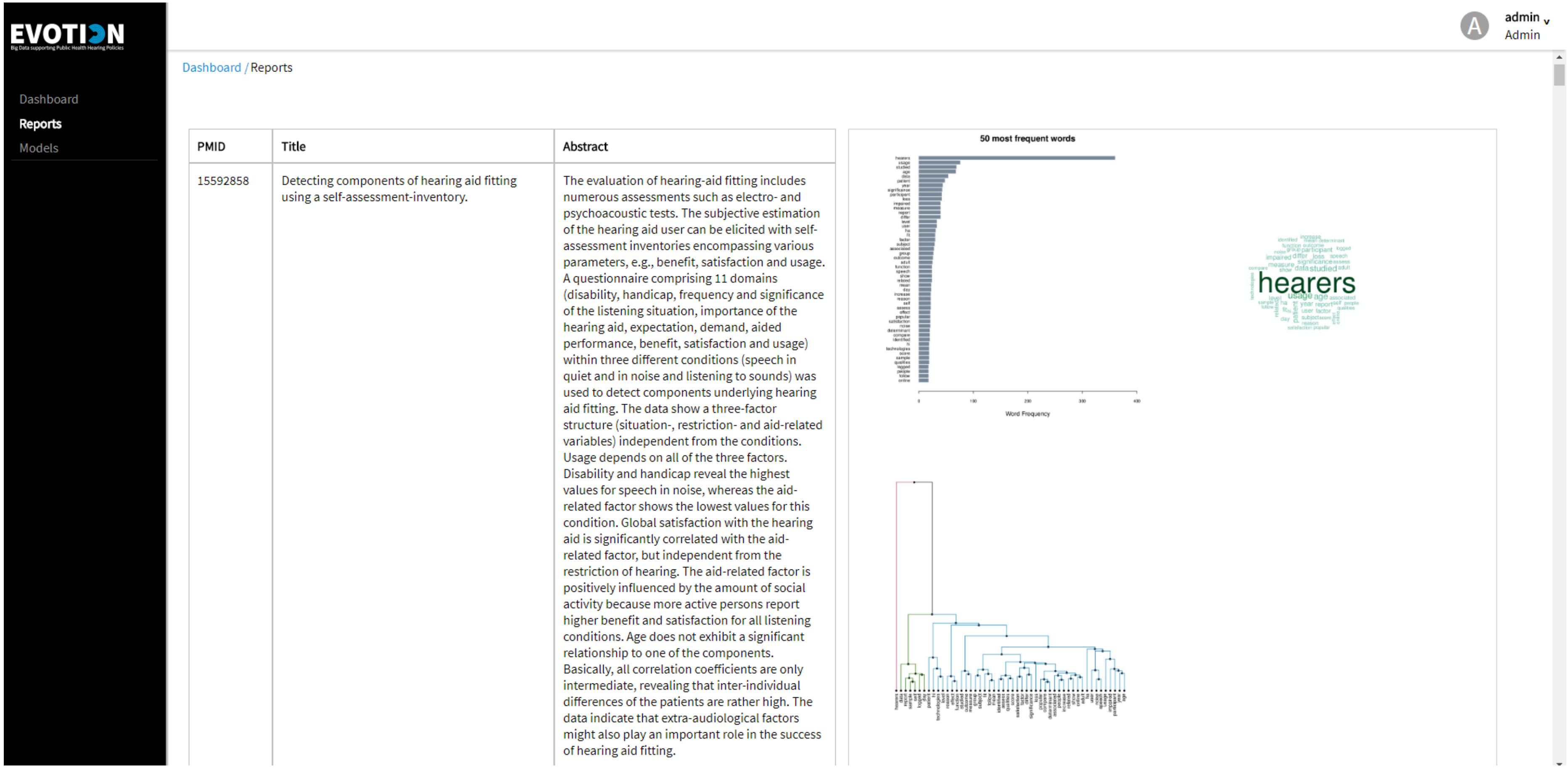

Figure 19 Example of Text-Mining Reports Page

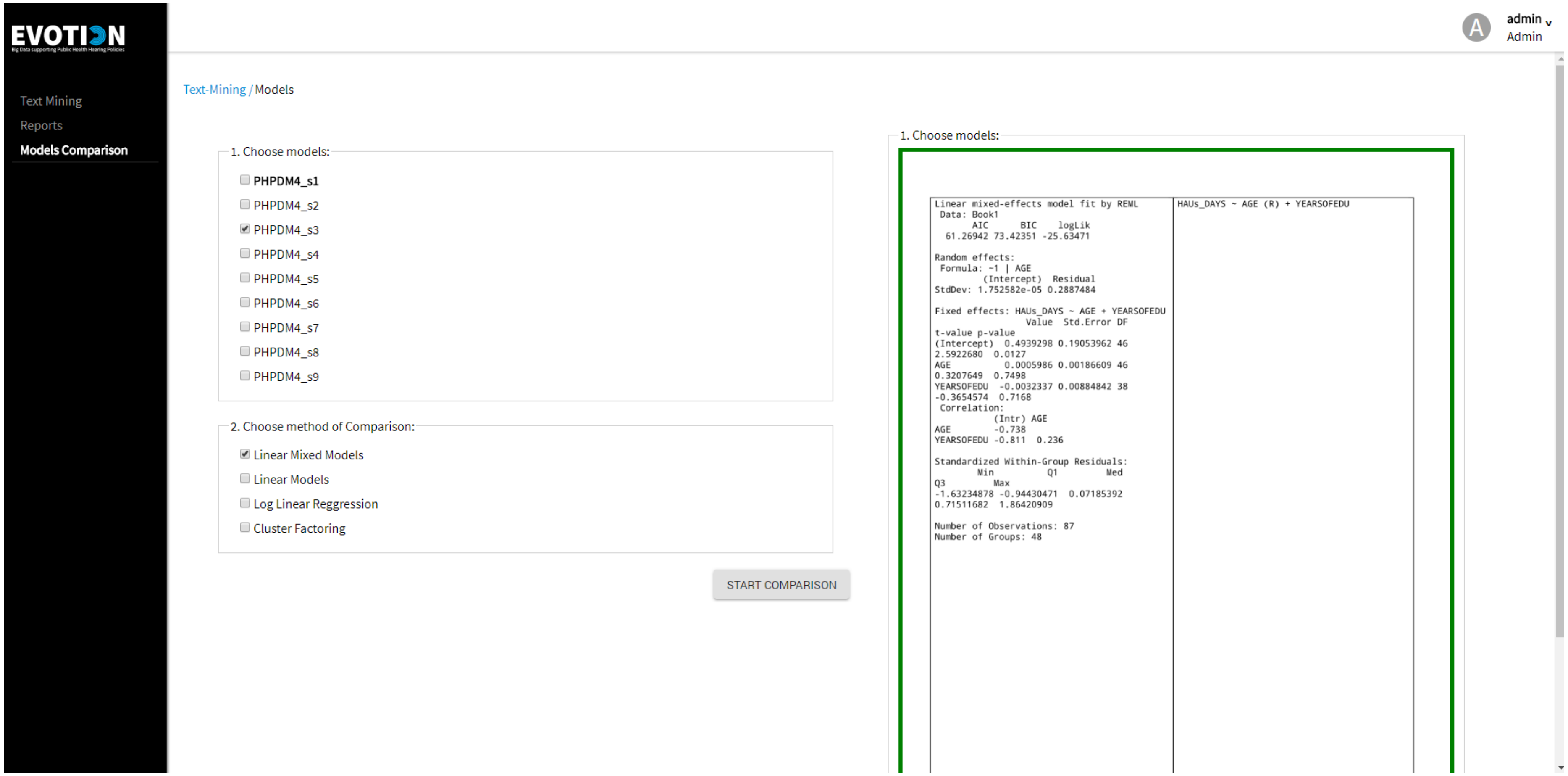

Figure 20 Model-Comparison Page

8 Use Cases and Demonstrator

8.1 Example of Applying the Text-Mining Component to the PHPDMs

The first version of the four (4) PHPDMs as presented in D3.1 (Katrakazas et al., 2017) identified interconnections among the EVOTION monitored data, which were characterized as an EVOTION Data (ED) – Factor (F) relation. These relations are shown in the following tables (Tables 5-8, colour code is adapted from D3.1):

Table 5 PHPDM1 EVOTION data and factors

EVOTION Data	EVOTION factors
Hearing aid usage	Environment
Hearing aid satisfaction	Noise
	Outdoor Activities
	Location
	Education
	Significant Others
	Age
	Gender
	Personal Care
	Civil Status
	Smoking
	Diabetes
	Obesity
	Ototoxicity
	Cause
	Heart Rate
	Respiratory Rate
	MOCA
	Reaction Time
	Forward Digit Recall
	Reverse Digit Recall
	HADS
	Occupation
	Employment

Table 6 PHPDM2 EVOTION data and factors

EVOTION Data	EVOTION factors
Noise Induced Hearing Loss (NIHL)	Pure Tone Audiometry
Occupational Noise	Hearing Aid Usage
Social Noise	
Permanent Threshold Shift (PTS)	
Temporary Threshold Shift (TTS)	
Sound Pressure Level	

Table 7 PHPDM3 EVOTION data and factors

EVOTION Data	EVOTION factors
GHABP	Auditory Training Type
Hearing Aid Use	Auditory Training Dosage
MOCA	Education
Listening Effort	

Table 8 PHPDM4 EVOTION data and factors

EVOTION Data	EVOTION factors
MOCA	Diabetes
HUI3	Smoking
Hearing aid usage	Vascular disease
	Dementia
	Occupation
	Education
	Age
	Reading Span
	Verbal reaction time
	Mood monitoring
	Reverse digit Recall
	HADS
	Social Engagement

One of the first tasks of the Text-Mining Component was to identify whether there is a meaningful relationship among the aforementioned connections. In simpler terms, we tried to identify whether there is common literature for each one of the ED-F connections. As these concepts are purely clinically-related, the bibliographic database of PubMed was used.
Identification of common literature among different areas is commonly applied to Hypotheses Generation, where text-mining methods are applied to suggest associations between the different areas. Therefore, the following scale has been designed on the basis that if the two key areas are mentioned in a large number of papers then the link between these areas is stronger. In addition, a colour-code is used to indicate a no, weak, potential and strong connection between ED and F:

- No connection: number of publications = 0 (no colour)
- Weak connection: number of publications <10 (light red colour)
- Potential connection: number of publications <50 (light yellow colour)
- Strong connection: number of publications >50 (light green colour)

Based on the aforementioned settings, we examined all the possible connections of the key areas mentioned in the PHPDMs and filtered the results in order to include bibliography related to "humans" but excluding "children" and "cochlear implants", which are out of the scope of the current project. The reason for working like that, is that PubMed uses indexing terms (not just MeSH terms but also keywords) and so the search needs to be a more restrictive to reduce the number of false positives. For this specific task, we did not specify a timespan for our search (meaning that the TM component would look into all articles published including the given keywords). There was also no restriction regarding the language (English and non-english literature was searched). An indicative example of the search function of the TM component with the keywords “hearing aid usage” and “noise” is the following:

```
("hearing aids"[MeSH Terms] OR ("hearing"[All Fields] AND "aids"[All Fields]) OR "hearing aids"[All Fields] OR ("hearing"[All Fields] AND "aid"[All Fields]) OR "hearing aid"[All Fields]) AND usage[All Fields] AND ("noise"[MeSH Terms] OR "noise"[All Fields])
```

Tables 9-22 show the results of this simple TM task.

Table 9 PHPDM1 Literature-Review Results for Hearing Aid Usage

PHPDM1 Key Areas	Keywords	No of Articles	Filtering
Hearing Aid Usage	Environment	24	16
	Noise	50	36
	Outdoor Activities	1	0
	Location	2	2
	Education	25	13
	Significant Others	4	4
	Age	83	43
	Gender	23	15
	Personal Care	9	6
	Civil Status	0	0
	Smoking	0	0
	Diabetes	0	0
	Obesity	0	0
	Ototoxicity	0	0
	Heart Rate	0	0
	Respiratory Rate	0	0
	MOCA	0	0
	Reaction Time	3	3
	Forward Digit Recall	0	0
	Reverse Digit Recall	0	0
	HADS	0	0
	Occupation	0	0
	Employment	1	1

Table 10 PHPDM1 Literature-Review Results for Hearing Aid Satisfaction

PHPDM1 Key Areas	Keywords	No of Articles	Filtering
Hearing Aid Satisfaction	Environment	124	68
	Noise	265	144
	Outdoor Activities	1	0
	Location	10	5
	Education	77	43
	Significant Others	58	27
	Age	236	122
	Gender	41	27
	Personal Care	57	40
	Civil Status	0	0
	Smoking	0	0
	Diabetes	0	0
	Obesity	0	0
	Ototoxicity	0	0
	Heart Rate	0	0
	Respiratory Rate	0	0
	MOCA	0	0
	Reaction Time	5	1
	Forward Digit Recall	0	0
	Reverse Digit Recall	0	0
	HADS	1	0
	Occupation	7	4
	Employment	12	7

Table 11 PHPDM2 Literature-Review Results for Noise Induced Hearing Loss

PHPDM2 Key Areas	Keywords	No of Articles	Filtering
Noise Induced Hearing Loss	Pure Tone Audiometry	865	604
	Audiogram	2634	1921
	Hearing Aid Usage	5	3

Table 12 PHPDM2 Literature-Review Results for Occupational Noise

PHPDM2 Key Areas	Keywords	No of Articles	Filtering
Occupational Noise	Pure Tone Audiometry	570	467
	Audiogram	1810	1584
	Hearing Aid Usage	3	2

Table 13 PHPDM2 Literature-Review Results for Social Noise

PHPDM2 Key Areas	Keywords	No of Articles	Filtering
Social Noise	Pure Tone Audiometry	68	48
	Audiogram	237	146
	Hearing Aid Usage	7	5

Table 14 PHPDM2 Literature-Review Results for Permanent Threshold Shift

PHPDM2 Key Areas	Keywords	No of Articles	Filtering
Permanent Threshold Shift	Pure Tone Audiometry	49	26
	Audiogram	123	54
	Hearing Aid Usage	2	2

Table 15 PHPDM2 Literature-Review Results for Temporary Threshold Shift

PHPDM2 Key Areas	Keywords	No of Articles	Filtering
Temporary Threshold Shift	Pure Tone Audiometry	87	60
	Audiogram	223	139
	Hearing Aid Usage	2	2

Table 16 PHPDM3 Literature-Review Results for GHABP

PHPDM3 Key Areas	Keywords	No of Articles	Filtering
GHABP	Auditory Training Type	0	0
	Auditory Training Dosage	0	0
	Education	6	1

Table 17 PHPDM3 Literature-Review Results for Hearing Aid Use

PHPDM3 Key Areas	Keywords	No of Articles	Filtering
Hearing Aid Use	Auditory Training Type	52	11
	Auditory Training Dosage	2	0
	Education	1423	457

Table 18 PHPDM3 Literature-Review Results for MOCA

PHPDM3 Key Areas	Keywords	No of Articles	Filtering
MOCA	Auditory Training Type	2	2
	Auditory Training Dosage	0	0
	Education	366	262

Table 19 PHPDM3 Literature-Review Results for GHABP

PHPDM3 Key Areas	Keywords	No of Articles	Filtering
Listening Effort	Auditory Training Type	6	3
	Auditory Training Dosage	0	0
	Education	62	29

Table 20 PHPDM4 Literature-Review Results for MOCA

PHPDM4 Key Areas	Keywords	No of Articles	Filtering
MOCA	Diabetes	100	72
	Smoking	22	22
	Vascular disease	267	245
	Dementia	444	339
	Occupation	40	4
	Education	367	262
	Age	630	421
	Reading Span	1	1
	Verbal reaction time	4	3
	Mood monitoring	2	1
	Reverse digit Recall	1	0
	HADS	14	7
	Social Engagement	4	3

Table 21 PHPDM4 Literature-Review Results for HUI3

PHPDM4 Key Areas	Keywords	No of Articles	Filtering
HUI3	Diabetes	23	15
	Smoking	4	2
	Vascular disease	17	12
	Dementia	7	5
	Occupation	2	1
	Education	30	20
	Age	132	61
	Reading Span	0	0
	Verbal reaction time	0	0
	Mood monitoring	0	0
	Reverse digit Recall	0	0
	HADS	1	1
	Social Engagement	0	0

Table 22 PHPDM4 Literature-Review Results for Hearing Aid Usage

PHPDM4 Key Areas	Keywords	No of Articles	Filtering
Hearing aid usage	Diabetes	0	0
	Smoking	0	0
	Vascular disease	0	0
	Dementia	0	0
	Occupation	2	0
	Education	28	9
	Age	88	33
	Reading Span	0	0
	Verbal reaction time	0	0
	Mood monitoring	0	0

PHPDM4 Key Areas	Keywords	No of Articles	Filtering
	Reverse digit Recall	0	0
	HADS	0	0
	Social Engagement	1	1

These results indicate that a refining process based on existing literature provides a more meaningful insight to the PHPDMs, as far as the public health point-of-view is concerned. As some parameters are found to have a stronger connection inside a PHPDM's framework, it indicates that these parameters should be of priority when examining the application of different policies. Nonetheless, it should also be noted that lack of existing common literature between two key concepts, does not necessarily mean that these concepts are not associated.

Therefore, the new suggested PHPDMs based on a TM approach are updated to the versions shown in Fig. 22 (a data-driven model representation has been selected to indicate the strong, potential and weak link of the main key concept with the identified factors, namely the s, p and w function representation).

8.2 Example of simulation/prediction functionalities

The current example is meant to illustrate how the DSS can:

1) identify relevant factors for hearing aid usage (PHPDM1) and
2) predict occupational/social noise (PHPDM2) from age, education and pure tone audiometry according to Figure 7 in D5.6.

For this illustrative case, sound environment measurements (see section 2.2.3 and Table 2 in D5.1 (Li et al., 2017)) from early-access data, representing a sub-sample of the EVOTION data, are used. The data quantifies the sound environment by 21 parameters (e.g. SPL, Noise floor and SNR) logged every 1 minute. Figure 1 and 2 presents examples of some of the parameters. In addition to the sound environment data, each of the included participants had a pure tone audiometry done prior to hearing aid (HA) fitting.

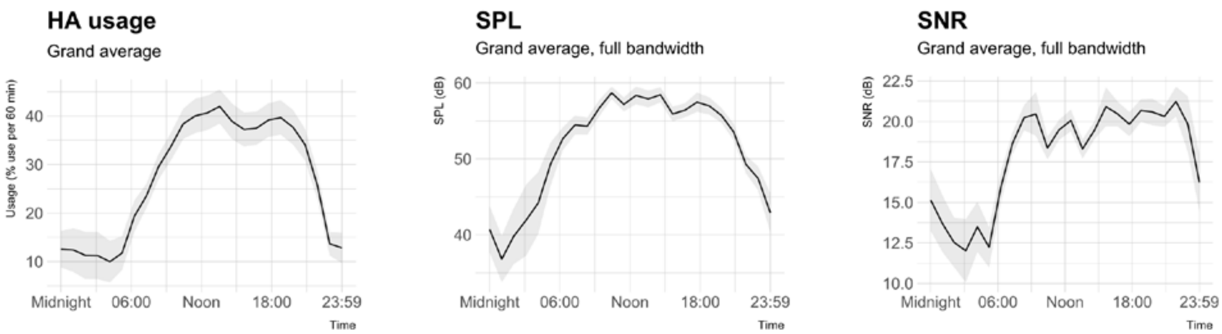

Figure 21 Grand average (and SEM) HA data logged by the participants.

1. PHPDM1
    1. $Hearing\ Aid\ Usage\ =\ p(environment, noise, age, education, gender) + w(location, significant\ others, personal\ care, reaction\ time, employment)$
    2. $Hearing\ Aid\ Satisfaction\ =\ s(environment, noise, age) + p(education, significant\ others, gender, personal\ care) + w(location, reaction\ time, occupation, employment)$

2. PHPDM2
    1. $Noise\ Induced\ Hearing\ Loss = \ s(pure\ tone\ audiometry, audiogram) + w(hearing\ aid\ usage)$
    2. $Occupational\ Noise = \ s(pure\ tone\ audiometry, audiogram) + w(hearing\ aid\ usage)$
    3. $Social\ Noise = \ s(audiogram) + p(pure\ tone\ audiometry) + w(hearing\ aid\ usage)$
    4. $Permanent\ Threshold\ Shift = \ s(audiogram) + p(pure\ tone\ audiometry) + w(hearing\ aid\ usage)$
    5. $Temporary\ Threshold\ Shift = \ s(pure\ tone\ audiometry, audiogram) + w(hearing\ aid\ usage)$

3. PHPDM3
    1. $GHABP = \ w(education)$
    2. $Hearing\ Aid\ Usage = \ s(education) + p(auditory\ training\ type)$
    3. $MOCA = \ s(education) + w(auditory\ training\ type)$
    4. $Listening\ Effort = \ p(education) + w(auditory\ training\ type)$

4. PHPDM4
    1. $HUI3 = \ s(age) + p(diabetes, vascular\ disease, education) + w(smoking, dementia, occupation)$
    2. $Hearing\ Aid\ Usage = \ p(age) + w(education, social\ engagement)$
    3. $MOCA = s(diabetes, vascular\ disease, dementia, education, age) + p(smoking) + w(occupation, reading\ span, verbal\ reaction\ time, mood\ monitoring, HADS, social\ engagement)$

Figure 22 Updated Version of PHPDMs based on TM (data-driven models representation)

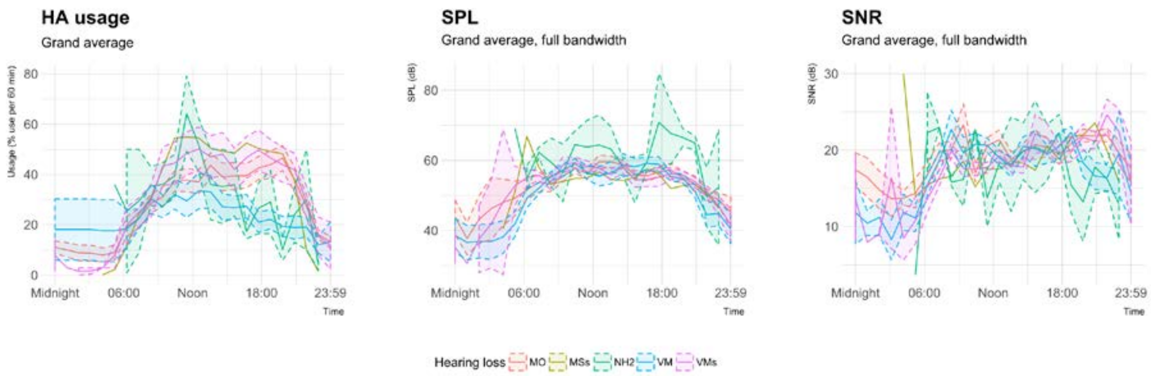

Figure 23: Grand average (and SEM) HA data logged by the participants and separated for degree of hearing loss indexed by IEC 60118-15.
MO: Moderate; MSs: Moderate/severe w. slope; NH2: Normal -10dB; VM: Very mild; VMs: Vey mild w. slope.

According to PHPDM1 in Fig. 22, Hearing Aid Usage (HAu) (i.e. the percentage of a day, split into 24 hours, where a hearing aid is active), might be predicted by the relation:

$$Hearing\ Aid\ Usage = p(environment, noise, age, education, gender) + w(location, significant\ others, personal\ care, cause, reaction\ time, employment)$$

Visual inspection of the data (Fig. 22 and 23) suggests that HAu increases over the course of a day. Both SPL and SNR increase with time, and we can set up models to verify possible relations, and identify the relevant factors of $p(environment, noise)$ – that is, factors of the sound environment that significantly affect HAu. In addition, the DSS can include factors of the degree of hearing, which might modulate how the sound environment affects HAu:

$$Hearing\ Aid\ Usage = p(environment, noise) + w(hearing\ loss)$$

In the above relation, $p(environment, noise)$ is represented by the measured full-bandwidth sound pressure levels (SPL) and signal-to-noise ratios (SNR) averaged across 1-hour epochs and days (Fig. 21). Moreover, $w(hearing\ loss)$ is represented by the degree of hearing loss on the left ear (HL) as a 10-step scale as indexed by IEC 60188-15 (Bisgaard et al., 2010) (Fig. 23), and by the pure tone average (PTA, 0.5 – 8 kHz) across both ears (Allen and Eddins, 2010).

By using a LMM (McCulloch and Neuhaus, 2001), we can assume that the random, mixed effects are either due to time (i.e. HAu is varying over the period of 24 hours simply due to time), or due to different baseline HAu's among the participants (i.e. a *random intercept* model (McCulloch and Neuhaus, 2001)). Thus, the full models, which might account for HAu across participants (1) or across time (2) with linear combinations of factors are in *R* syntax:

(1) $HAu \sim SPL + SNR + HL + PTA + (1 \mid \mathrm{Hour})$
(2) $HAu \sim SPL + SNR + HL + PTA + (1 \mid \mathrm{Participant})$

In addition to the above stated models, hearing loss and sound environment might interact to predict HAu (e.g., people with worse hearing loss might use their HAs more even in less noisy environments), which leads to the following two models (an interaction between factors are specified by "$*$" in *R*):

(3) $HAu \sim (SPL + SNR) * (HL + PTA) + (1 \mid \text{Hour})$
(4) $HAu \sim (SPL + SNR) * (HL + PTA) + (1 \mid \text{Participant})$

To identify the most significant factors, each of the full models are compared with null models and with various parameterizations considering separate factors. To compare the models and find the best combination of factors, Akaike's Information Criterion (*AIC*) is inspected. *AIC* is given by:

$$AIC = 2k - 2\ln(L),$$

where *k* denotes the number of factors going in to the model and *L* denotes the maximized value of the likelihood function (i.e. how well the model fits the observations on a relative scale). Thus, the model with the *lowest AIC* is preferred (regardless of whether the compared models are nested or not).

In this example,HAu across participants are considered (i.e. *random intercept* model, Equation 2 and 4 above). This means that the results will indicate if the chosen factors affect HAu over the course of a day. First, relevant sound environment factors are identified by comparing different parameterizations of the full model. From the output of the model comparisons (Fig. 24), the combination of SPL and SNR (M.3) achieves the lowest *AIC* and this model is therefore preferred. The null model is compared to a model assuming HAu is predicted by SNR (M.1), SPL (M.2), or by a combination of SNR and SPL (M.3). The best (lowest) AIC is found for the combination of SPL and SNR, however, the addition of SNR did not result in a significant improvement of model M.2 (p = 0.093).

```
Models:
M.NULL: HAu ~ 1 + (1 | Participant)
M.1: HAu ~ SNR + (1 | Participant)
M.2: HAu ~ SPL + (1 | Participant)
M.3: HAu ~ SPL + SNR + (1 | Participant)
       Df    AIC    BIC  logLik deviance   Chisq Chi Df Pr(>Chisq)
M.NULL  3 6770.1 6784.1 -3382.1   6764.1
M.1     4 6764.8 6783.5 -3378.4   6756.8  7.3021      1   0.006887 **
M.2     4 6717.7 6736.4 -3354.9   6709.7 47.1047      0  < 2.2e-16 ***
M.3     5 6716.9 6740.2 -3353.5   6706.9  2.8223      1   0.092964 .
```

Figure 24: Models to identify relevant sound environment factors (output from R).

Next, the same procedure is used to identify the best fitting combination of sound environment and hearing loss factors to account for HAu. From the output (Fig.25), the preferred model is M.2b, which assumes that the sound environment (SNR + SPL) is interacting with the degree of hearing loss, as indexed by PTA, to account for HAu. The combination of SPL and SNR (M.3) is extended with factors for hearing loss. The best fitting model is to assume that a combination of HL and PTA interacts with the sound environment to account for HAu (M.4b).

```
Models:
M.NULL: HAu ~ 1 + (1 | Participant)
M.1b: HAu ~ (SPL + SNR) + PTA + (1 | Participant)
M.2b: HAu ~ (SPL + SNR) * PTA + (1 | Participant)
M.3b: HAu ~ (SNR + SPL) + HL + (1 | Participant)
M.4b: HAu ~ (SNR + SPL) + (HL + PTA) + (1 | Participant)
M.5b: HAu ~ (SPL + SNR) * HL + (1 | Participant)
M.6b: HAu ~ (SNR + SPL) * (HL + PTA) + (1 | Participant)
       Df    AIC    BIC  logLik deviance   Chisq Chi Df Pr(>Chisq)
M.NULL  3 6770.1 6784.1 -3382.1   6764.1
M.1b    6 6718.0 6745.9 -3353.0   6706.0 58.1853      3  1.435e-12 ***
M.2b    8 6715.6 6752.9 -3349.8   6699.6  6.3235      2    0.04235 *
M.3b    9 6720.5 6762.4 -3351.2   6702.5  0.0000      1    1.00000
M.4b   10 6722.3 6768.9 -3351.2   6702.3  0.1446      1    0.70370
M.5b   17 6722.1 6801.3 -3344.0   6688.1 14.2423      7    0.04704 *
M.6b   20 6716.7 6809.9 -3338.4   6676.7 11.3412      3    0.01002 *
```

Figure 25: Models (in order of increasing complexity) to identify most relevant factors of hearing aid use (HAu) (output from R).

The final step is to examine if the identified model is significantly better than a null model assuming no modulation of HAu (M.NULL) over the course of a day. The output of this comparison is shown in Fig. 26. A highly significant result indicates that HAu are significantly modulated by the interaction between sound environment (SPL + SNR) and degree of hearing loss (HL + PTA). Since the *p*-value is very small (p = 1.417e-12), the conclusion is that a linear combination of the sound environment (SPL + SNR) and the degree of hearing loss (PTA) indeed affects HAu, and that the best model is to assume an interaction, i.e. that the effect of sound environment on HAu is modulated by the degree of hearing loss. This is also, what a visual inspection of Figure 23 (left) would suggest: MO, MSs, and VMs seem to diverge from the other categories of hearing loss from noon to evening.

```
Models:
M.NULL: HAu ~ 1 + (1 | Participant)
M.2b: HAu ~ (SPL + SNR) * PTA + (1 | Participant)
       Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
M.NULL  3 6770.1 6784.1 -3382.1   6764.1
M.2b    8 6715.6 6752.9 -3349.8   6699.6 64.509      5  1.417e-12 ***
```

Figure 26: Comparing the null model with the selected model M.4c.

A summary of the final preferred model (see Figure 27) can then inform about the impact of the factors to HAu. From the summary, the residual variance (i.e. the variance in HAu not explained by the model) is down to 276.4 from 300.8 of the null model. In addition, SNR contributed the most to HAu, increasing it by 0.87 (±0.35) pp.

```
Random effects:
 Groups      Name        Variance Std.Dev.
 Participant (Intercept) 176.3    13.28
 Residual                276.4    16.62

Fixed effects:
             Estimate Std. Error t value
(Intercept)  3.725349  14.194976   0.262
SPL          0.084330   0.234929   0.359
SNR          0.873262   0.346698   2.519
PTA         -0.099211   0.333892  -0.297
SPL:PTA      0.010553   0.005480   1.926
SNR:PTA     -0.016561   0.007967  -2.079
```

Figure 27: Model summary of the preferred model to account for HAu.

8.3 Example of primary model instance selection on a PHPDM

Based on the version of the PHPDMs shown in Fig. 22 and following Section 5.2's model selection criteria, we present a final example to test the validity of the aforementioned criteria for a number of model instances, based in early acquired datasets related to PHPDM4. Since this section serves as an example, we will not use an extensive dataset-reliant model, but a simple one, consisting of 87 early acquired sets of numerical data for this example. These data were scrambled and randomized to produce a new dataset used for the purposes of this example. It should also be noted that this analysis is to take place after any BDA calculations and model evaluations, therefore the final selection methodology is going to be described here.

One of the key parameters of PHPDM4 is that of Hearing Aid Usage, which is described by the following relationship:

$$Hearing\ Aid\ Usage \sim p(age) + w(education, social\_engagement) \tag{13}$$

Based on (13), the following instances stem from the model:

Table 23 PHPDM4 Instances Comparison for HAUs

#	Model Description
s1	HAUs ~ AGE + EDUCATION
s2	HAUs ~ AGE + SOCIAL ENGAGEMENT
s3	HAUs ~ EDUCATION + SOCIAL ENGAGEMENT
S1	HAUs ~ AGE + EDUCATION + SOCIAL ENGAGEMENT

We also assume a consistent form of the data, as the one shown in the following table:

Table 24 Example of Consistency in Data formats

YEARSOFEDU	AGE	HAUs_DAYS	SOCENG
12	71	0.116666667	3
0	48	0.220654932	1
14	78	0.59671114	4
17	51	0.864583333	2

LLM will allow the suggestion of a size that expresses HAUs and can be correlated with all the parameters to resolve the problem. This will show if these parameters can be estimated in HAUs and how much they contribute to the prediction of each variable, having a strong or not correlation with the desired concept (i.e. HAUs).

Selecting the LLM method to be applied in the s1-3 and S1 instances, with a different variable parameter each time (in total nine models arise from these selections, the DSS will yield the results found in Appendix. Out of these instances, a public health policy maker should choose the model with the lower AIC, which is:

$$s3: Hearing\ Aid\ Usage\ \sim Education + \ Social\ Engagement \qquad (14)$$

The interesting outcome of this first-level analysis, is that although bibliography indicated a stronger connection among hearing aid usage and age, education and social engagement factors from a data-analysis point-of-view give a better indication of hearing aid usage levels. Therefore, correlation among these three datasets should be investigated further and in accordance with related public policy actions.

At this point, it should be clarified that the final version of PHPDMs is yet to be finalized (upcoming deliverables D3.2 and D3.3 in M24/36) as well as the PHPDM Specification/Transformation Tools (upcoming deliverables D4.2 and D4.3 in M24/36)). Therefore, the previous example was simply used to demonstrate the envisioned capabilities of the DSS upon the completion of the aforementioned deliverables.

8.4 Demonstrator Section

The demonstration part of this deliverable is a video available at the EVOTION website: http://h2020evotion.eu/?ddownload=789 showing the functionality of the administrator DSS Dashboard. It should be noted that the presented Dashboard will not be offered to the final user(s), but only to the EVOTION super Administrator.

The DSS developed in the present deliverable will be integrated at the CITY premises in order to provide access at a consortium level, as agreed in the consortium according to the relative security and privacy framework of the EVOTION project.

Conclusion

The plea for more evidence-based decision making in hearing health has been around for some time – and has largely remained unfulfilled to date. One of the reasons is that comprehensive information on hearing-health related factors intertwined with the opportunity to make objective comparisons between potential interventions have simply not been available.

EVOTION is likely to provide a game-change in this respect, by developing a Decision Support System (DSS) to support hearing health policy making at several levels. A framework featuring relevant –usually multiple – links between hearing health related factors and models, as the latter have been developed in EVOTION, along with their scientifically proven impact – is hereby established to facilitate the quest for more effective hearing health related strategies in the future.

This report outlined the first successful steps towards a public-health policy-driven DSS. The DSS presented here is a complete, pre-final deployment, including all the architectural components for supporting the execution of text-mining and model-comparison tasks, driven from the PHPDM instances. The EVOTION DSS is unique in its setting and once finalised will close a substantial gap in the hearing health related public-health policy decision-making community. Figure 28 shows the capabilities of the EVOTION DSS as far the pre- and post-model operations are concerned.

Extended functionalities of the DSS are planned to be included in the future as the project progresses towards a full integration and upon completion of the remaining components of the EVOTION platform. These extensions include (i) predefined scenarios to support public-health policy decisions (ii) model-simulation and comparison algorithms based on the updated versions of PHPDMs and (iii) enabling/support prioritization of interventions, based on the final format of PHPDMs that will provide criteria to be used for selecting a policy. Example of such a criterion might help in cases where a model (or an instance of it) is statistically weak but has a strong policy impact role.

This document is complemented by a video demonstrating the DSS administrator dashboard and two indicative examples of the DSS functionalities: a text-mining and a model selection operation. These artefacts along with the present report constitute the complete version of Deliverable D5.6.

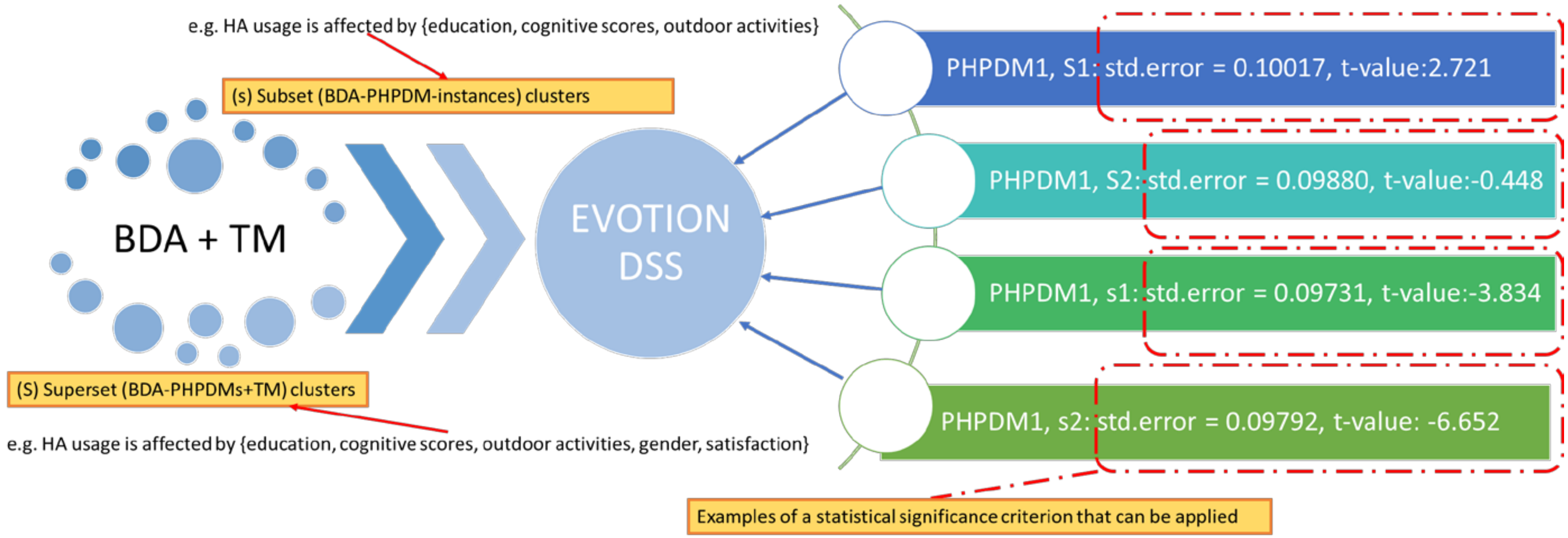

Figure 28 Pre-and Post-Model Operations of the EVOTION DSS

References

Allen, P.D., Eddins, D.A., 2010. Presbycusis phenotypes form a heterogeneous continuum when ordered by degree and configuration of hearing loss. Hear. Res. 264, 10–20. https://doi.org/10.1016/j.heares.2010.02.001

Anisetti, M., Bellandi, V., Cremonini, M., Damiani, E., Dimakopoulos, N., Kokkinakis, P., Papagrigoriou, P., Smyrlis, M., Pontoppidan, N.H., 2018. Big Data Analytics Engine, Deliverable D5.5 to the EVOTION-727521 Project funded by the European Union. University of Milan, Milan, Italy.

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.

Bisgaard, N., Vlaming, M.S.M.G., Dahlquist, M., 2010. Standard Audiograms for the IEC 60118-15 Measurement Procedure. Trends Amplif. 14, 113–120. https://doi.org/10.1177/1084713810379609

Boisvert, I., Clemesha, J., Lundmark, E., Crome, E., Barr, C., McMahon, C.M., 2017. Decision-Making in Audiology: Balancing Evidence-Based Practice and Patient-Centered Care. Trends Hear. 21. https://doi.org/10.1177/2331216517706397

De Savigny, D., Adam, T., Alliance for Health Policy and Systems Research, World Health Organization (Eds.), 2009. Systems thinking for health systems strengthening. Alliance for Health Policy and Systems Research ; World Health Organization, Geneva.

Dimakopoulos, N., Giotis, G., Kokkinakis, P., Economou, A., Fritaki, M., Gavalas, G., Prasinos, M., Smith, A., Spanoudakis, G., Papagrigoriou, P., Stefanakis, M., Koloutsou, N., Murdin, L., Katrakazas, P., Koutsouris, D., Brdarić, D., Milas, J., Dudarewicz, A., Pawlaczyk-Łuszczyńska, M., Śliwińska-Kowalska, M., Zaborowski, K., Laplante-Lévesque, A., Memic, A., Pontoppidan, N.H., Kaloyanova, G., Trenkova, L., Tsokova, N., Bamiou, D.-E., Dritsakis, G., Anisetti, M., Bellandi, V., Cremonini, M., Damiani, E., Bibas, A., Kikidis, D., 2017. EVOTION stakeholders, scenarios, and requirements, Confidential Deliverable D2.1 to the EVOTION-727521 Project funded by the European Union. Athens Technology Center, Athens, Greece.

Gałecki, A., Burzykowski, T., 2013. Linear Mixed-Effects Models Using R: A Step-by-Step Approach, Springer Texts in Statistics. Springer-Verlag, New York.

Hudspeth, W.B., Budge, A., 2013. Using Satellite-Based Earth Science Data in a Public Health Decision-Support System to Track and Forecast Pollen Events. AGU Fall Meet. Abstr. 21, IN21C-1399.

Katrakazas, P., Androutsou, T., Milas, J., Brdarić, D., Dudarewicz, A., Pawlaczyk-Łuszczyńska, M., Śliwińska-Kowalska, M., Smith, A., Murdin, L., Koloutsou, N., Pontoppidan, N.H., Trenkova, L., Kaloyanova, G., Tsokova, N., Bamiou, D.-E., Dritsakis, G., Bibas, A., Kikidis, D., teset, 2017. Public Health Policy Decision Models (PHPDM) v1, Deliverable D3.1 to the EVOTION-727521 Project funded by the European Union. Institute of Communications and Computer Systems, Athens, Greece.

Li, X., Pontoppidan, N.H., Hafez, A., 2017. EVOTION hearing aids, Confidential Deliverable D5.1 to the EVOTION-727521 Project funded by the European Union. Eriksholm Research Centre, Oticon A/S, Snekkersten, Denmark.

McCulloch, C.E., Neuhaus, J.M., 2001. Generalized linear mixed models. Wiley Online Library.

Mera, M., González, C., Blobel, B., 2015. A public health decision support system model using reasoning methods. Stud. Health Technol. Inform. 211, 255–262.

Pizzi, N.J., 2013. A public health decision support system framework using approximate reasoning methods, in: 2013 Joint IFSA World Congress and NAFIPS Annual Meeting (IFSA/NAFIPS). Presented at the 2013 Joint IFSA World Congress and NAFIPS Annual Meeting (IFSA/NAFIPS), pp. 128–133. https://doi.org/10.1109/IFSA-NAFIPS.2013.6608387

Prasinos, M., Spanoudakis, G., Basdekis, I., Smith, A., Anisetti, M., Cremonini, M., Katrakazas, P., Androutsou, T., Ioannidou, P., 2017. PHPDM model specification language, Confidential Deliverable D4.1 to the EVOTION-727521 Project funded by the European Union. CITY University, London, United Kingdom.

Talib, R., Hanif, M.K., Ayesha, S., Fatima, F., 2016. Text Mining: Techniques, Applications and Issues. Int. J. Adv. Comput. Sci. Appl. Ijacsa 7. https://doi.org/10.14569/IJACSA.2016.071153

Tarnowska, K., Ras, Z.W., Jastreboff, 2017. Decision Support System for Diagnosis and Treatment of Hearing Disorders - The Case of Tinnitus [WWW Document]. URL https://www.springer.com/gp/book/9783319514628 (accessed 6.15.18).

Yazdani, S., Jadidfard, M.-P., 2016. Developing a decision support system to link health technology assessment (HTA) reports to the health system policies in Iran. Health Policy Plan. czw160. https://doi.org/10.1093/heapol/czw160

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.

Appendix

Results from running LLM on PHPDM4’s HA_USAGE parameter:

<table>
<tr><th>Model Version in R syntax</th><th>Results as an R output</th></tr>
<tr><td>HAUs_DAYS ~ AGE (R) + YEARSOFEDU</td><td>Linear mixed-effects model fit by REML
 Data: Book1
      AIC   BIC   logLik
  61.26942 73.42351 -25.63471

Random effects:
 Formula: ~1 | AGE
        (Intercept) Residual
StdDev: 1.752582e-05 0.2887484

Fixed effects: HAUs_DAYS ~ AGE + YEARSOFEDU
                 Value Std.Error DF   t-value p-value
(Intercept) 0.4939298 0.19053962 46 2.5922680 0.0127
AGE   0.0005986 0.00186609 46 0.3207649 0.7498
YEARSOFEDU -0.0032337 0.00884842 38 -0.3654574 0.7168
 Correlation:
           (Intr) AGE
AGE   -0.738
YEARSOFEDU -0.811 0.236

Standardized Within-Group Residuals:
        Min   Q1   Med   Q3
Max
-1.63234878 -0.94430471 0.07185392 0.71511682 1.86420
909

Number of Observations: 87
Number of Groups: 48</td></tr>
<tr><td>HAUs_DAYS ~ AGE + YEARSOFEDU (R)</td><td>Linear mixed-effects model fit by REML
 Data: Book1
      AIC   BIC   logLik
  61.02113 73.17522 -25.51057

Random effects:
 Formula: ~1 | YEARSOFEDU
        (Intercept) Residual
StdDev: 0.05525277 0.2855983

Fixed effects: HAUs_DAYS ~ AGE + YEARSOFEDU
                 Value Std.Error DF   t-value p-value
(Intercept) 0.4487655 0.19972408 77 2.2469275 0.0275
AGE   0.0005465 0.00185766 77 0.2941876 0.7694
YEARSOFEDU -0.0005463 0.00994619 7 -0.0549213 0.9577
 Correlation:
           (Intr) AGE
AGE   -0.684
YEARSOFEDU -0.812 0.178

Standardized Within-Group Residuals:
        Min   Q1   Med   Q3
Max
-1.71018121 -0.90463677 0.07199187 0.72125430 1.90148
311</td></tr>
</table>

<table>
<tr><th>Model Version in R syntax</th><th>Results as an R output</th></tr>
<tr><td></td><td>Number of Observations: 87
Number of Groups: 9</td></tr>
<tr><td>HAUs_DAYS ~ AGE (R) + SOCENG</td><td>Linear mixed-effects model fit by REML
Data: Book1
AIC BIC logLik
57.47052 69.62461 -23.73526

Random effects:
Formula: ~1 | AGE
(Intercept) Residual
StdDev: 1.633282e-05 0.2860609

Fixed effects: HAUs_DAYS ~ AGE + SOCENG
Value Std.Error DF t-value p-value
(Intercept) 0.3631472 0.12417160 46 2.9245593 0.0053
AGE 0.0005655 0.00180257 46 0.3137118 0.7552
SOCENG 0.0350423 0.02670557 38 1.3121727 0.1973
Correlation:
(Intr) AGE
AGE -0.815
SOCENG -0.456 -0.082

Standardized Within-Group Residuals:
Min Q1 Med Q3
Max
-1.78970980 -0.83548855 0.07683988 0.68406465 1.88911
626

Number of Observations: 87
Number of Groups: 48</td></tr>
<tr><td>HAUs_DAYS ~ AGE + SOCENG (R)</td><td>Linear mixed-effects model fit by REML
Data: Book1
AIC BIC logLik
57.47052 69.62461 -23.73526

Random effects:
Formula: ~1 | SOCENG
(Intercept) Residual
StdDev: 1.235086e-05 0.2860609

Fixed effects: HAUs_DAYS ~ AGE + SOCENG
Value Std.Error DF t-value p-value
(Intercept) 0.3631472 0.12417160 82 2.9245593 0.0045
AGE 0.0005655 0.00180257 82 0.3137117 0.7545
SOCENG 0.0350423 0.02670557 2 1.3121727 0.3198
Correlation:
(Intr) AGE
AGE -0.815
SOCENG -0.456 -0.082

Standardized Within-Group Residuals:
Min Q1 Med Q3
Max
-1.78970981 -0.83548855 0.07683987 0.68406464 1.88911
625

Number of Observations: 87
Number of Groups: 4</td></tr>
</table>

Model Version in R syntax	Results as an R output
HAUs_DAYS ~ YEARSOFEDU (R) + SOCENG	Linear mixed-effects model fit by REML Data: Book1 AIC BIC logLik 54.15827 66.31235 -22.07914 Random effects: Formula: ~1 | YEARSOFEDU (Intercept) Residual StdDev: 0.05084191 0.2833388 Fixed effects: HAUs_DAYS ~ YEARSOFEDU + SOCENG Value Std.Error DF t-value p-value (Intercept) 0.4066075 0.15798262 77 2.5737481 0.0120 YEARSOFEDU -0.0010299 0.00957939 7 -0.1075105 0.9174 SOCENG 0.0339269 0.02655972 77 1.2773816 0.2053 Correlation: (Intr) YEARSO YEARSOFEDU -0.879 SOCENG -0.430 0.023 Standardized Within-Group Residuals: Min Q1 Med Q3 Max -1.8623828 -0.8831090 0.1501505 0.7213092 1.9024958 Number of Observations: 87 Number of Groups: 9
HAUs_DAYS ~ YEARSOFEDU + SOCENG (R)	Linear mixed-effects model fit by REML Data: Book1 AIC BIC logLik 54.31244 66.46652 -22.15622 Random effects: Formula: ~1 | SOCENG (Intercept) Residual StdDev: 1.444734e-05 0.2859776 Fixed effects: HAUs_DAYS ~ YEARSOFEDU + SOCENG Value Std.Error DF t-value p-value (Intercept) 0.4438204 0.14639547 82 3.0316541 0.0033 YEARSOFEDU -0.0032747 0.00852923 82 -0.3839441 0.7020 SOCENG 0.0351578 0.02664944 2 1.3192705 0.3179 Correlation: (Intr) YEARSO YEARSOFEDU -0.871 SOCENG -0.493 0.056 Standardized Within-Group Residuals: Min Q1 Med Q3 Max -1.7843606 -0.8865329 0.1058005 0.7006271 1.8706389 Number of Observations: 87 Number of Groups: 4
HAUs_DAYS ~ AGE (R) + YEARSOFEDU + SOCENG	Linear mixed-effects model fit by REML Data: Book1 AIC BIC logLik 66.99797 81.51101 -27.49899 Random effects: Formula: ~1 | AGE (Intercept) Residual

<table>
<tr><th>Model Version in R syntax</th><th>Results as an R output</th></tr>
<tr><td></td><td>StdDev: 1.7488e-05 0.287604

Fixed effects: HAUs_DAYS ~ AGE + YEARSOFEDU + SOCENG
                 Value Std.Error DF   t-value p-value
(Intercept) 0.4127831 0.19990386 46 2.0649080 0.0446
AGE   0.0004277 0.00186339 46 0.2295258 0.8195
YEARSOFEDU -0.0028039 0.00881962 37 -0.3179163 0.7523
SOCENG   0.0347202 0.02686873 37 1.2922144 0.2043
 Correlation:
           (Intr) AGE   YEARSO
AGE   -0.676
YEARSOFEDU -0.781 0.233
SOCENG   -0.314 -0.071 0.038

Standardized Within-Group Residuals:
        Min   Q1   Med   Q3
Max
-1.78405833 -0.85365994 0.09369616 0.70173871 1.89114
129

Number of Observations: 87
Number of Groups: 48</td></tr>
<tr><td>HAUs_DAYS ~ AGE + YEARSOFEDU (R) + SOCENG</td><td>Linear mixed-effects model fit by REML
 Data: Book1
       AIC   BIC   logLik
  66.85743 81.37047 -27.42871

Random effects:
 Formula: ~1 | YEARSOFEDU
        (Intercept) Residual
StdDev: 0.04991623 0.2850584

Fixed effects: HAUs_DAYS ~ AGE + YEARSOFEDU + SOCENG
                 Value Std.Error DF   t-value p-value
(Intercept) 0.3791822 0.20650549 76 1.8361847 0.0702
AGE   0.0004014 0.00185651 76 0.2162018 0.8294
YEARSOFEDU -0.0007139 0.00976121 7 -0.0731315 0.9437
SOCENG   0.0335833 0.02677082 76 1.2544753 0.2135
 Correlation:
           (Intr) AGE   YEARSO
AGE   -0.641
YEARSOFEDU -0.780 0.183
SOCENG   -0.290 -0.064 0.012

Standardized Within-Group Residuals:
       Min   Q1   Med   Q3   Max
-1.8646974 -0.8674750 0.1289001 0.7131440 1.9187378

Number of Observations: 87
Number of Groups: 9</td></tr>
<tr><td>HAUs_DAYS ~ AGE + YEARSOFEDU + SOCENG (R)</td><td>Linear mixed-effects model fit by REML
 Data: Book1
       AIC   BIC   logLik
  66.99797 81.51101 -27.49899

Random effects:
 Formula: ~1 | SOCENG
         (Intercept) Residual
StdDev: 1.561534e-05 0.287604</td></tr>
</table>

<table>
<tr><th>Model Version in R syntax</th><th>Results as an R output</th></tr>
<tr><td></td><td><pre>
Fixed effects: HAUs_DAYS ~ AGE + YEARSOFEDU + SOCENG
                 Value Std.Error DF   t-value p-value
(Intercept) 0.4127831 0.19990386 81 2.0649080 0.0421
AGE   0.0004277 0.00186339 81 0.2295258 0.8190
YEARSOFEDU -0.0028039 0.00881963 81 -0.3179163 0.7514
SOCENG   0.0347202 0.02686874 2 1.2922144 0.3255
 Correlation:
           (Intr) AGE   YEARSO
AGE   -0.676
YEARSOFEDU -0.781 0.233
SOCENG   -0.314 -0.071 0.038

Standardized Within-Group Residuals:
        Min   Q1   Med   Q3
Max
-1.78405833 -0.85365995 0.09369615 0.70173871 1.89114
129

Number of Observations: 87
Number of Groups: 4
</pre></td></tr>
</table>