Public health policy for management of hearing impairments based on big data analytics: EVOTION at Genesis

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***Abstract*— The holistic management of hearing loss (HL) requires appropriate public health policies for HL prevention, early diagnosis, long-term treatment and rehabilitation; detection and prevention of cognitive decline; protection from noise; and socioeconomic inclusion of HL patients. However, currently the evidential basis for forming such policies is limited. Holistic HL management policies require the analysis of heterogeneous data, including Hearing Aid (HA) usage, noise episodes, audiological, physiological, cognitive, clinical and medication, personal, behavioural, life style, occupational and environmental data. To utilise these data in forming holistic HL management policies, EVOTION, a new European research and innovation project, aims to develop an integrated platform supporting: (a) the analysis of related datasets to enable the identification of causal and other effects amongst them using various forms of big data analytics, (b) policy decision making focusing on the selection of effective interventions related to the holistic management of HL, based on the outcomes of (a) and the formulation of related public health policies, and (c) the specification and monitoring of such policies in a sustainable manner. In this paper, we describe the EVOTION approach.**

Keywords*— *Public health policy; hearing loss; hearing aids; big-data analysis

I. MOTIVATION

A. *Hearing Loss and its consequences*

Hearing Loss (HL) is the most frequent sensory deficit and one of the most prevalent chronic diseases, affecting approximately one-third of people over the age of 65 and over 5% of the world's population [16]. In 2014, WHO estimated that in 2012 more than 360 million people had disabling HL, i.e., a 3-fold increase from 120 million in 1995 [16]. HL ranks as the fifth leading cause of Years Lived with Disability (YLD), a component of the Disability-Adjusted Life Year (DALY), used to measure the global burden of disease [1]. This ranking is higher than diabetes and conditions causing visual impairment [1]. Current trends in the spread of HL are expected to continue or increase further due to exposure to workplace and social noise. In the UK, for example, the percentage of people suffering from HL is expected to exceed 20% of the overall population by 2031 [2].

The consequences of HL in the overall health condition of the people suffering from it are significant. Several studies have shown that HL increases the risk of cognitive decline/dementia by 20% [3], mental illness [4], depression [4], and even the risk of mortality due to reduced physical and mental activity and social isolation [5][6]. The latter factors also lead to a poorer quality of life overall both in physical and mental terms for HL patients [8]. Furthermore, HL increases the risk of accidental injury (e.g. HL is associated with incidents of falls [3]).

The economic consequences of HL are also significant. In particular, HL results in reduced productivity, unemployment or early retirement, loss of income and work discrimination [10]. Studies in health economics also indicate that the treatment of HL has a significant cost. According to [8], for instance, the annual cost of HL in the European Union is €213bn.

B. *Challenges in HL management*

Currently, the pre-eminent management strategy for HL is the provision of Hearing Aids (HAs). Modern HAs are programmable sound amplification devices that are worn by hearing impaired to overcome their hearing deficits. HAs can detect and classify types of sound environments (e.g., quiet, noisy or windy environments; listening to speech or music) and manually or automatically switch between different settings, to optimise hearing of the patients who wear them in such environments. Despite these capabilities, however, the currently available HAs can only partially overcome the deficits associated with HL and their users face several challenges. More specifically, HA users frequently find it difficult to select amongst pre-defined settings of HAs [9]. They also find their HAs difficult to accustom and frequently ineffective. Consequently, they need to visit their clinician several times for HA adjustments and often end up not using their HAs. Some of the most commonly reported reasons for the non-usage of HAs, include the ineffectiveness of HAs in noisy situations, due to poor sound quality and perceived benefit. Despite the fact that new generation HAs support a wide variety of advanced programming settings, literature suggests that older adults do not use these as they are less able to decide on complex circumstances and alternatives [10]. Therefore, the majority (80%) of adults aged 55 to 74 years who would benefit from a HA, do not use them [10], and nearly 30% of HA users are dissatisfied with their HAs in noisy situations [11].

The key reason underpinning ineffective HA use is that HAs are fitted to suit the audiogram rather than the patient's needs and overall profile. Ideally, HA fitting should take into account: (a) a range of personal and real life behavioural, physiological and other auditory related data; and (b) an analysis of the circumstances which are challenging for individual HA users on a continuous basis. It should also be appropriately supported by individualised rehabilitation treatments such as auditory training [12], as HA users depend more on their cognitive resources than normal hearing listeners in order to understand speech [13]. Nevertheless, evidence on how to link such information with appropriate, individualised management strategies is still lacking.

C. Need and role of public policy

The effective management of HL depends on and requires appropriate public health policies (PHP) [1][2]. Public health policy affects the affordability and hence access to HAs and ongoing treatment services (e.g., HL check-ups, HA adjustments, provision of related rehabilitation services). Public health policy can also have a significant effect on:

- the prevention and early diagnosis of HL;
- the early treatment of diagnosed HL through the provision of Has and other assistive devices;
- the longer-term treatment of HL through systematic checks of the hearing, the provision of other vital related rehabilitation services including auditory training and hearing therapy;
- the protection of people with hearing impairments from the harmful effects of loud noise; and
- the early detection, delay or even prevention of cognitive decline; the set-up of standards, services and technology for promoting and ensuring inclusion of participation of HL patients with in various settings (e.g., at work, at school/educational establishments, in everyday life).

On-going reforms of PHP in this area (e.g., changes in the free provision of HAs for different types of HL in the UK) and the spark of social debate that they have caused demonstrate the importance of PHP in this area. Examples of policy fields that influence big part of the population and mobilize resources encountered in billions of euros yearly are cut off points of hearing aid fitting covered by insurance, decision for unilateral or bilateral HA fitting or cochlear implantation, noise protection measures in working environments, and default maximum dB levels of electronic devices.

The management of HL and its consequences at a public health policy making level can benefit from the analysis of heterogeneous data, including HA usage, noise episodes causing threshold shifts, audiological, physiological, cognitive, clinical and medication, personal, behavioural, life style data, occupational and environmental data. The analysis of these types of data using big data analytic techniques can enable the investigation of whether HL relates to other comorbidities and contextual factors and patterns of such relations.

The outcomes of such analysis can also enable the stratification of related risks and effects to HL patients, and – through correlation with other economic, social and physical constraints – help developing a holistic systemic perspective of over interventions regarding the management of HL. Moreover, it can enable the broader support, social and occupational inclusion and the well-being of HL patients, exploration of missing, under or over-estimated value of specific interventions (e.g. noise protection, visualization of public announcements etc.) and analysis of their effectiveness.

II. The EVOTION Vision

The overall aim of EVOTION is to enable the types of analysis identified in *Sect. I.C* and support evidence based public health policy formation.

EVOTION aims to do support this through, the development of an integrated platform incorporating a big data analytics (BDA) platform, which will enable the collection and analysis of heterogeneous data related to hearing loss, including hearing aid usage, physiological, cognitive, medical, personal, occupational, behavioural, life style, environmental and open web data. These data will underpin a decision support system to the identification, simulation, selection and monitoring of the effectiveness of possible and implemented interventions related to the management of hearing loss and the overall inclusion and well-being of HL patients in processes aimed at the formulation of related public health policies, based on the outcomes of the BDA.

The EVOTION platform will support decisions related to the formation of public health policies for HL treatment. These policies may cover aspects such as:

- HL treatment rationalisation, including for example policies for: (a) the provision of HAs and HA usage monitoring and adjustment to increase the frequency and efficacy of HA use and to reduce wastage of underused HAs; (b) enhancing post HA provision care (aka follow up care), remote care and self-management (e.g., remote adjustment of HAs to improve access of HA users to audiology care services and reduce the cost of the latter); (c) HL rehabilitation services (e.g., cognitive rehabilitation/auditory training); and/or (d) treating HL as a long-term condition and in an integrated manner based on multi-morbidity long term indicators.

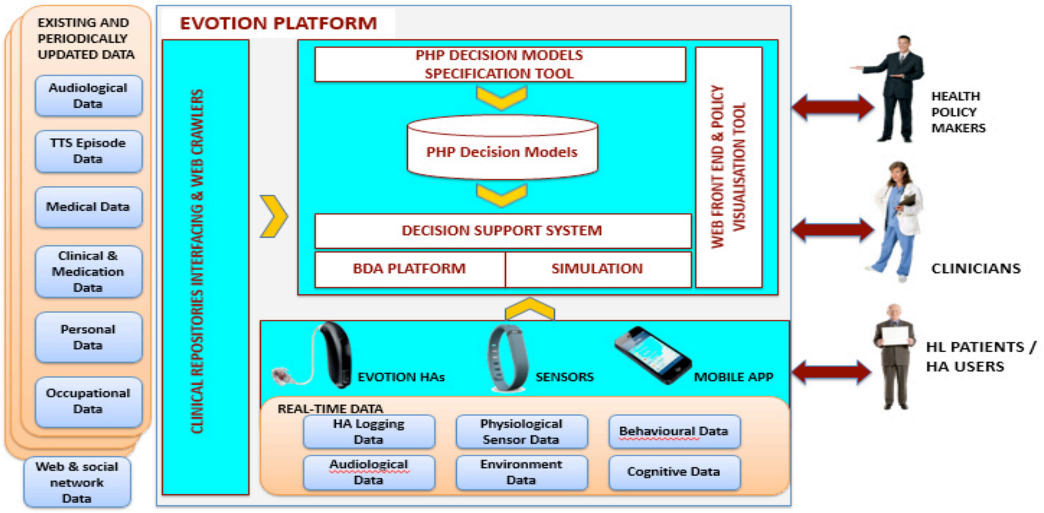

Figure 1. EVOTION platform, information flows and decision marking

- Investigating potential causal mechanisms of HL comorbidities, and identifying profiles and multi-level factors whose coexistence multiplies risks of HL deterioration and/or comorbidities occurrence, in order to judge – based on evidence – whether specific interventions have worthwhile effects in fields related to HL.
- Screening/ early detection of HL, including detection of noise induced hearing loss (NIHL)
- Improving the wider health system from the perspective of HL, including for example policies for improving access to non-HL related health services for HL patients
- Enhancing the inclusion of HL patients, including, for example, policies for: (a) using assisted listening devices (ALDs) in public spaces and public transport to support good communication, and (b) addressing communication challenges for HL patients in occupational contexts (e.g., incentives for use of ALDs and alternative visual signals in work spaces)
- Improving the safety of HL patients, including policies for improving hearing whilst driving and walking
- Improving the overall well-being of HL patients including, for example, policies aiming to enable/increase physical activity of HL patients.
- Prevention of noise induced hearing loss, social isolation and cognitive decline arising from HL

III. The EVOTION Platform

To achieve its overall aim, EVOTION aims to build a platform that will integrate:

- Existing *clinical repositories* of HL related data including personal, medical and occupational data already available at the clinical institutions participating in EVOTION.
- *Enhanced HAs* enabling the capture and provision of HA usage related data (e.g., rating of HA ease or difficulty of use in different listening conditions, frequency and type adjustments of HA controls).
- *Wearable sensors* supporting the collection real time contextual HA user physiological data (e.g., heart rate, blood pressure, skin conductance)
- A *mobile application* with components supporting the acquisition and transmission of: (a) behavioural and life style data (e.g., recording of HA user daily activities such as participation in conversations, watching TV); (b) contextual data (e.g., HA user's location); (c) cognitive data (e.g., verbal reaction time); and (d) subjective data provided by HA user and/or their carers regarding interventions; and the execution of periodic audiological and cognitive tests to collect the related data (audiological and cognitive test components)
- A *big data analytics (BDA) platform* enabling the analysis of data collected by the platform, through the use of data mining, statistical, text and social media data analysis techniques.
- A *simulation* component enabling the specification and execution of predictive models regarding the potential outcomes of different policy alternatives.
- A *decision support system (DSS)* enabling the suggestion of decisions to policy making stakeholders as justified by the supporting evidence arising from the big data analytics, and the execution of simulation models.
- A public health policy decision marking *(PHPDM) models specification tool* supporting the specification of models that can drive the decision-making process (see Sect. IV below).
- A *social media analysis tool* enabling the publication of public health policy issues and prospective policy decisions (along with supporting evidence) and the acquisition and analysis of social network data regarding the views of patients and the wider public over these issues and the related policies.

The main components, overall information flow, big data analytics, decision support capabilities policy making platform envisaged by EVOTION are shown in Figure 1.

The data collected by the EVOTION solution will be correlated and analysed, using BDA techniques, which will be employed in order to detect patterns of:

(a) Contextualised HA usage and its effectiveness for different types of HL patients (in reference to the environment and the activities carried out by HL patients)
(b) Contextualised TTS episode occurrences for different types of HL patients and effectiveness of existing preventive measures (e.g. noise protection)
(c) Contextualised cognitive capabilities for different types of HL patients
(d) Correlations between different factors and comorbidities affecting HL and the overall well-being of HL patients suffering from it

In detecting (a)–(d), our key focus will be to identify factors and parameters that define subgroups with different treatment outcomes, and the risks arise for such subgroups and the outcomes.

The EVOTION platform will support its users to specify the types of analysis that they would like to apply upon the data collected by the platform in a declarative form, as well as the forms in which the outcomes of this analysis can be visualised, the certainty thresholds that these outcomes should exceed in order to be deemed usable in the decision-making process, and the criteria in which they can inform the selection of policy alternatives. The forms of BDA that will be performed by the EVOTION platform and the usage of its outcomes will be specified as part of PHPDM models (see Sect. IV below).

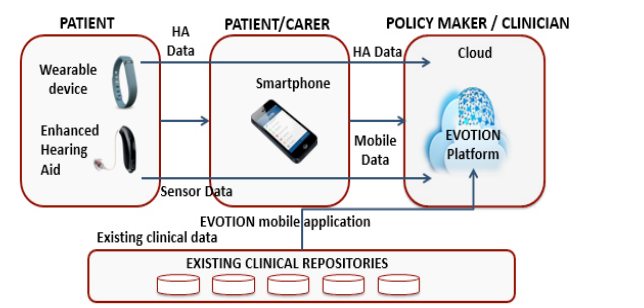

Figure 2 Envisaged physical architecture of EVOTION platform

The envisaged physical architecture of the EVOTION solution is shown in Figure 2. As shown in the figure, EVOTION will be deployed on a cloud infrastructure and the and accept retrospective and prospective (dynamic) data from different components, including existing clinical repositories, the mobile application that will be part of the platform, enhanced HAs and wearable devices (biosensors) available off-the-shelf. EVOTION HAs will be communicating with the EVOTION application to send real time HA usage and environment data to it, and receive adaptation control signals from it. This will be through the mobile application or directly to the platform (for HA users who do not have mobile phones). Wearable biosensors will also be sending data to the EVOTION platform, through either the mobile phone or directly to the platform. The EVOTION platform will also be capable of connecting and receiving existing and periodically updateable data from existing clinical repositories (e.g., outcomes of audiograms and other hearing aid fitting tests, clinical questionnaires etc.).

IV. Public Health Policy Decision Making Models

The operation of the EVOTION platform will be driven by public health policy decision-making models (PHPDM models). These models will specify:

(i) the *generic goal(s)* underpinning the decision to be made (e.g. policies regarding the frequency of follow up care for patients who have been issued HAs) and the alternative decisions that may be made for this goal (e.g., having no, one or two follow ups within a specific time period)
(ii) the *criteria* to be used for making such decisions (e.g., whether the difficulties faced by different types of HA users depend on the type of their HL, their cognitive capabilities, their life style and behaviour, other comorbidities that they may have and/or their overall compliance with HA usage guidelines given to them by clinicians and whether such difficulties are alleviated depending on the number of follow up treatments and the time that elapses between them)
(iii) the *BDA evidence* required for applying the criteria (e.g., whether any combination of the factors considered above is a good predictor of the difficulties faced by HA users as confirmed by specific types of statistical analysis or data mining based classification) and the BDA process for producing it
(iv) *simulations* that should be executed for exploring the consequences of alternative decisions
(v) *processes* to be followed for making specific types of health policies (e.g., what is the threshold of evidence that should be considered sufficient for a particular decision, who are the stakeholders whose views should be considered and recorded prior to reaching a decision, who has responsibility for making the final decision, whether a decision should be continually or periodically reviewed upon the acquisition of new evidence etc.)

These models will also provide a structure for organising possible alternative decisions in policy making, the arguments and rationale for making decisions, the stakeholders participating in the decision-making process, the views they express and the final decision making rules. Hence, PHPDM models will drive a collaborative stakeholder decision making process, and provide a structure for recording information that will make it traceable and accountable. Furthermore, PHPDM models will be specified parametrically to make their customisation easy in case that this would be required in different policy making settings. Thus, PHPDM models can be repeatedly executed in the same or different policy making settings (e.g., for making policy on the very same issues in different regions).

The EVOTION platform will provide a tool supporting the specification of PHPDM models into some high-level language. Their verification and transformation into executable BDA and simulation tasks and decision making processes would be passed as inputs to the BDA platform, simulator and decision support system of the platform to execute them and realize the policy making process specified by them.

The PHPDM models covering the aspects identified above will be automatically transformed into executable BDA processes and simulation processes whose execution would provide the basic evidence required for making a decision and exploring its consequences.

V. Related Work

The development of the EVOTION platform is related to the several scientific and clinical research areas, the most prominent of which are (a) public health policy making and (b) big data analytics and decision making. In the following, we present an overview of research in (a) and (b).

A. Public health policy making

The World Health Organization (WHO) defines "health policy" as the "decisions, plans, and actions that are undertaken to achieve specific health care goals within a society" [16]. Research on public health policy making has primarily focused on policy formation processes and guidelines. These may be related to four key stages in policy making, namely: (i) situational analysis (i.e., the assessment of the needs and gaps, the resources available, and eventually the strengths weaknesses, opportunities and threats (SWOT) arising in connection with a situation that needs to be addressed by health policy); (ii) development of action plan (i.e., setting the initial aim, objectives, activities and all priorities for implementing a health policy programme, and identifying the resources needed for this implementation); (iii) implementation and monitoring of programme; and (iv) programme evaluation (i.e., the assessment of the effects and other outcomes of implemented health policy programme in long/medium term).

The Canadian Foundation for Healthcare Improvement (CFHI) has developed a framework of 18 processes to support Evidence-Informed Health Policymaking [19]. These processes are aimed at ensuring that relevant research is identified, appraised and used to inform health policy decisions. CFHI guidelines cover all stages (i)-(iv) above, albeit (ii) more comprehensively WHO has developed a manual for planning and monitoring national health strategies, aimed at raising awareness about ear and hearing problems among individuals and communities. These have been tailored and targeted separately to the general public, policy-makers, programme managers and funding providers [18]. WHO's guidelines focus on use of SWOT in situational analysis, suggest aims for the development of action plans, identify sub-phases in implementation and monitoring (i.e., pilot, expansion and evaluation). The applicability and transferability of evidence (ATE) tool [20][21] has been developed to help health planners make decisions about local health planning priorities. ATE focuses mainly on directing investigations of the literature as part of public health policy decision making to aid situational analysis.

Although public health policy has a profound effect on health status, there is a considerable gap between what research shows as effective and the policies that are enacted and enforced. Research is most likely to influence policy development through an extended process of communication and interaction [23]. Systematic reviews of studies of decision-making by health care policy-makers show that researchers could better inform health care management and policy-making by making several changes to how they produce and update systematic reviews and by adapting existing reviews that are relevant to local health care issues [27]. Also, according to a study on systematically reviewing qualitative and quantitative evidence to inform management and policy-making, policy-makers and managers increasingly require access to high-quality evidence syntheses that include research and non-research evidence, and both qualitative and quantitative research findings [28].

The use of BDA has significant potential in reducing the costs of health care in several areas, including: high-cost patients, re-admissions, decompensation, adverse events, and treatment optimisation for diseases affecting multiple organ systems [24]. Further benefits from the use of BDA in healthcare include the potential for generating new knowledge, enabling personalised medicine, delivering information directly to patients and empowering them to play a more active role [25]. However, a prerequisite for successful learning from big health care data is to gain actionable insights into evidence generated by the data [26].

B. Big data analytics

BDA can be separated into three parts (input, data analytics, and output) and seven operators (gathering, selection, pre-processing, transformation, data mining, evaluation, and interpretation). Nowadays, the data that need to be analysed are not just large, they are also composed of heterogeneous data types and real time streaming data. These characteristics make pre-processing an important task, and affect the applicability of statistical and data analysis approaches (as heterogeneous, incomplete and noisy and continually updated data affect the performance of the data analysis algorithms) [22].

Various solutions are available for BDA. These can be divided into (1) Processing/Compute (e.g., Hadoop [31], CUDA [32], and Twitter Storm [35]) (2) Storage (e.g., HDFS [33], HBase [34]), and (3) Analytics: MLPACK [29] or Mahout [30]. Although there are commercial products for data analysis, most of the studies on the traditional data analysis are focused on the design and development of efficient and/or effective "ways" to find the useful evidence in the data. Nevertheless, most of the current systems will not be able to handle the whole dataset all at once. Hence, designing a good data analytics framework becomes very important for the data analysis process. Data mining algorithms for data analysis also play a vital role in the BDA, in terms of the computation cost, memory requirement, and accuracy of the end results.

Machine learning (ML) and data mining (DM) algorithms are essential for BDA. However, many of these algorithms are designed for sequential and/ centralised computing. ML/DM research for BDA has focused on making ML/DM algorithms run on parallel platforms, such as Radoop [36] and Mahout [30]; and redesigning ML/DM algorithms (e.g., population-based algorithms) to make them suitable for parallel computing or to parallel computing environment (e.g., neural network algorithms for GPU and ant-based algorithm for grid). Despite these efforts, many research issues are still open including, for example, addressing communication cost for different computer nodes and the tackling the large computation cost of most ML/DM algorithms [22].

VI. Concluding Remarks

In this paper, we have introduced EVOTION, a new European research project, aims to develop an integrated platform supporting: (a) the analysis of related datasets to enable the identification of causal and other effects amongst them using various forms of big data analytics, (b) policy decision making focusing on the selection of effective interventions related to the holistic management of HL, based on the outcomes of (a) and the formulation of related public health policies, and (c) the specification and monitoring of such policies in a sustainable manner. In this position paper, we describe the EVOTION approach.

The main overall contribution of EVOTION to existing research will be the development of a novel model driven platform for establishing public health policies for the management of HL, based on evidence arising from the analysis of static and dynamic health data. Our focus on HL management and the availability of related big data sets in this area, gives our research a clear driver and background framework for evaluation. To the best of our knowledge, the above contributions are clearly beyond the current state of the art and introduce a significant innovation potential to the management and treatment of HL, hearing deterioration and related cognitive decay.

Beyond this, however, we believe that EVOTION has the potential to generate a generic platform for evidence based model driven public health policy making in other areas of healthcare, as well.

Acknowledgment

This work was partly supported by the EU-funded H2020 project EVOTION (grant no 727521).

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