Proposed Use of a Conversational Agent for Patient Empowerment

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Abstract: Empowerment is a process through which people acquire the necessary knowledge and self-awareness to understand their conditions and treatment options, make informed choices and self-manage their health conditions in daily life, in collaboration with medical professionals. Conversational Agents in healthcare could play an important role in the process of empowering a person but, so far, they have been seldom been used for this purpose. This paper presents the basic principles and preliminary implementation of a conversational health agent for patient empowerment. It dialogues with the user in a "natural" way, collects health data from heterogeneous sources and provides the user with specific and relevant information. This allows a person/patient to create his/her own opinion on health matters in the most complete and objective way, and, therefore, it facilitates the empowerment process.

1 INTRODUCTION

Technological innovations are accelerating disruption in consumer health and wellbeing but there is still a disconnect between current healthcare, focused on disease management, and the needs of empowered people whose focus is on comprehension and management of their health (Snowdon, 2020). An **empowered person/patient** 1. has the necessary knowledge and self-awareness to **understand** his/her conditions and treatment options, 2. can make **informed choices** *(i.e. decide)*, and 3. can **self-manage** his/her health conditions in daily life *(i.e. act),* in collaboration with medical professionals (European Health Parliament, 2017; WHO, 2016; Alfano et al., 2019a; Alfano et al., 2019b). Few applications exist for person/patient empowerment and they often work as silos (Snowdon, 2020).

Artificial Intelligence (AI) in healthcare can play an important role in the process of empowering a person (Kondyalkis et al., 2013; Iatraki et al. 2018). AI, however, often empowers machines rather than people (e.g., self-diagnosis apps tend to be substitute doctors and keep patients as passive recipients, Davenport and Kalakota, 2019; Jiang et al., 2017; Fast and Horvitz, 2017). Moreover, AI-driven healthcare applications are used in separated contexts, use different data, and work as silos (Herrero et al. 2016). Finally, the existing *virtual assistants* are mainly used for self-diagnosis (decide) and self-monitoring/management (act). Although they represent, in principle, the second and third step of the empowerment process, the first step (understanding) is unaddressed and, therefore, do not provide genuine empowerment (Magyar et al., 2019; Herrero et al., 2016).

How can AI be used to empower people and help them to better comprehend health information, make informed decisions and self-manage their health and wellbeing in collaboration with their healthcare professionals?

This paper presents the basic principles and preliminary implementation details of a conversational health agent for patient empowerment

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that facilitates the comprehension of health information so that a person can create his/her own opinion on health matters in the most complete and objective way, using the most accurate and appropriate information available. This is the first of the three empowerment steps and the precondition for the other two (i.e., making informed and conscious health decisions, together with medical professionals, and actively manage their health and well-being).

The paper is organized as follows. Section 2 illustrates the background and motivation of the research. Section 3 presents the principles of the conversational health agent for patient empowerment. Section 4 presents the details of the initial implementation of the agent. Sections 5 presents some conclusions and future work.

2 BACKGROUND AND MOTIVATION

2.1 Review of the Literature

Conversational agents or *chatbots* are computer programs that simulate conversations with users. These AI systems, also known as *relational agents*, inform the user by generating an easily comprehended dialogue.

We have made a preliminary analysis of the literature and we found only a limited number of studies linking person/patient empowerment to *conversational agents*: Issom et al. (2020) evaluated the information provided by a chatbot designed to help patients with Sickle-Cell Disease to prevent vaso-occlusive pain. Denecke et al. (2018a; 2018b) reported an AI-driven self-anamnesis mobile application in music therapy; a conversational user interface is chosen to simulate the patient-therapist conversation but there is no direct empowering action towards the patient.

We also searched for studies that connect AI or machine learning with patient empowerment and *conversational agents* used in healthcare. Ni et al. (2020) propose a model that predicts human physical activity status from sequential lifelogging data collected from wearable sensors. It can be used as a decision support tool to provide real-time monitoring, statistical analysis, and personalized advice. Yadav et al. (2020) present an AI-driven mobile application used to predict cases of Anaemia and Thalassemia. However, this application has been designed for use by a doctor, nurse, or a health worker, and not by a patient. The VASelfCare project (Magyar et al 2019) aimed to develop a *conversational agent* to facilitate the self-care of older adults with type 2 diabetes mellitus (T2D) by improving medication adherence and lifestyle changes (i.e., physical activity and diet). The counselling step is tailored through diverse pre-existing levels of knowledge, by means of a rule-based decision system. The *conversational agent* used *reinforcement* to learn appropriate behaviour based on users' preferences. Herrero et al. (2016) developed a portable personalised decision support system to empower individuals on insulin therapy to self-manage their condition. The blood glucose levels are collected by the sensors and are managed by a Case-Based Reasoning (CBR) module to provide personalised insulin recommendations, while a second Model-Based Reasoning (MBR) module is used to maximise users' safety. You and Gui (2020) conducted a review and interview study of eleven AI-enabled chatbot-based symptom checker (CSC) apps. They found that users perceive the current CSC apps to lack support for a comprehensive medical history, flexible symptom input, comprehensible questions, and diverse diseases and user groups.

Although limited, the review of the current literature shows:

- *Conversational agents* are mostly created for a specific condition.
- Empowerment is almost never addressed directly and, when it is, only some aspects are considered.
- Comprehension of the health information/conditions is the least addressed step of empowerment.
- Little user information is used to provide tailored content to the user.
- The origin of the provided content is often unknown and does not use all the information that is available, for example, on-line (Alfano et al. 2020b; Alfano et al. 2019c).
- User requirements, such as language level or information quality (Alfano et al. 2020a; Alfano et al. 2020b), are not considered.

Therefore, *conversational agents* currently focus on specific conditions and mainly deal with self-diagnosis or self-management of health/conditions. Almost no agent deals with person empowerment by considering the user characteristics and requirements, and then providing him or her with up-to-date and high-quality customized information.

2.2 Tailored Health Communication

Tailored health communication is the process of adapting information to the specific characteristics of an individual (Kamel Ghalibaf et al., 2019). Since it is more personally relevant, it is more likely to be read, understood, and acted on (Lustria et al., 2013; Noar et al., 2011). The process of tailoring health messages is the same as a tailor uses to make a custom-fit garment according to the customer's measurements and their preferred fabric, colour, and style. Likewise, tailored health communication considers the user's needs, interests, and concerns, to create appropriate "to fit" health information (Bol, Smit, & Lustria, 2020; Kreuter et al., 2000).

Interpersonal communication has the potential to be the most customized "tailored" type of communication, provided all participants understand, know, and listen to each other. Patients often complain that discussions with their doctor are unsatisfactory because they are frequently interrupted and not listened to (Snyder, 2008; Schouten & Meeuwesen, 2006). Ideally, for any health-related communication to be empowering it should support an attentive conversational dialogue with the user to assess his or her health needs and ensure any information provided is appropriate and comprehensible (Cheung et al., 2019); this applies both to traditional inter-personal and *conversational agents*.

2.3 Rationale for Tailored Health Information and Patient Empowerment

Although provision of tailored health information is often aimed at a change in behaviour (e.g., smoking cessation, dietary change, and physical activity), person empowerment already represents, by itself, a behavioural change (when it is seen as an outcome other than a process) because it provides a person with skills and "power" to make informed decisions, self-manage health and carry out further lifestyle changes as needed.

Petty and Cacioppo's Elaboration Likelihood Model (Petty and Cacioppo, 1981) provides a rationale for this approach (Kreuter et al., 1999):

1. *by tailoring materials, superfluous information is eliminated*
2. *the information that remains is more personally relevant to the message recipient*
3. *the message recipient will pay more attention to information he or she perceives to be personally relevant*
4. *information that is attended to is more likely to have an effect than that which is not*
5. *when attended to, information that addresses the unique needs of a person will be useful in helping him or her decide and act upon the decision.*

In addition, we believe the information provided to the user must be objective and factual and must not contain any kind of bias and opinion, unless explicitly required. In this way, a user will be able to create his or her own opinion without being influenced (even indirectly) by biased information.

3 CONVERSATIONAL HEALTH AGENTS FOR PATIENT EMPOWERMENT

The requirements of a conversational health agent that empowers users to understand health information, make informed decisions, self-manage their health and wellbeing, and interact better with healthcare professionals are:

- It **dialogues** with the user in the most "natural" way.
- It collects health data from **heterogeneous** sources (health information, health status, empowerment level, needs, etc.) and can understand, process, and combine them.
- It provides tailored information **that is specific and relevant to patients.**
- It provides a person/patient with **up-to-date** health information that is easy to understand and directly actionable.
- The information provided to the user is **objective and factual** and does not contain any kind of bias and opinion, unless explicitly required.
- It **explains** the principles on how information is selected in terms that a person/patient can understand, thus increasing his/her trust and acceptance.

On the **input** side, we assume that a user makes a query (clearly defined or undefined) about complaints or diseases. The system understands/establishes the **user query** and related **subqueries** in terms of:

- **Complaints -** re. definition, causes, related diseases, remedies.
- **Diseases -** re. presentation, related complaints, causes, treatment, prognosis, course of disease/ range of severity.

Moreover, the user provides further information (either directly or indirectly) that is going to be used as **explicit tailoring criteria** for the answer:

- **Current health status** (e.g., symptoms and/or conditions).
- **Background health status** (e.g., sex, age, gait, BMI, comorbid illness).
- **Lifestyle information** (e.g., sleep, drugs, meal composition, alcohol consumption, hormonal cycles).
- **Dynamic health indicators** (e.g., vital signs monitoring, physical activity monitoring, stress level).
- **Empowerment level** (health literacy, motivation, gaining control).

- **Health and wellbeing needs** (e.g., urgent health improvement, elective quality of life).

Notice that, beside the explicit tailoring criteria, we also consider some **implicit tailoring criteria** such as the **language level**, to provide the user with information he/she can easily understand (Alfano et al., 2020a; Alfano et al., 2020c; Alfano et al., 2018), and the **information quality**, in terms of selection of authoritative sources and factual (unbiased) information (Alfano et al., 2020b; Alfano et al., 2019a).

Possible **external sources** of health information are:

- Semantic Web (e.g., health-lifesci.schema.org).
- UMLS Metathesaurus.
- Specialized Websites.
- World Wide Web (selected sources).
- Other health information repositories.

We also consider **internal information** that comes from the user's previous data and from data related to other users (appropriately anonymized).

The system provides a **primary output** in terms of:

- **Tailored health information on complaints** (Definition, Causes, Related diseases, Remedies).
- **Tailored health information on diseases** (Presentation, Treatment, Prognosis, Course of disease/ Range of severity).

It also provides a **secondary output** in terms of:

- **Suggested available options** (based on a threshold mechanism) on talking to a doctor or going immediately to a hospital (Wasingya-Kasereka, 2020).
- **Connection** with relevant healthcare services and professionals.

The overall process of the conversational agent is summarised in Fig. 1 and works as follows:

1. The *conversational agent* receives the user input (query and tailoring data) through a dialogue interface.
2. The *conversational agent* processes the data, applies a decision rule algorithm, using the tailoring data, and retrieves the proper content from external repositories/databases.
3. The *conversational agent* provides the user with a primary and secondary output.
4. The user provides one of the following responses to the *conversational agent*:
   - Not OK, I did not get the required info.
   - Partially OK, Explain better.
   - OK, Explore further.
   - OK, Stop.

   For the first three responses, the user can provide additional information to better specify his/her further request.

   The system will then process the initial and new data (if present) and the user's previous responses (or responses of other users with a similar profile) and use a reinforcement learning algorithm to provide the new output.
5. The *conversational agent* provides the user with a new primary and secondary output and goes to step 4.

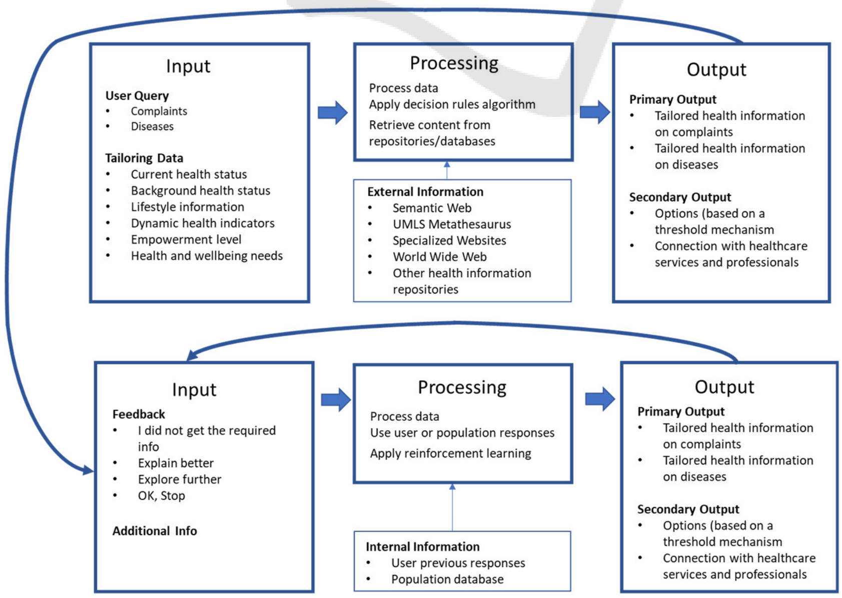

Figure 1: Summary of the process of the conversational health agent for person/patient empowerment.

4 INITIAL IMPLEMENTATION

The implementation of a conversational health agent for patient empowerment is currently being piloted.

4.1 Complaints and Diseases

There are only a finite number of symptoms and signs of a disease. For our implementation we have used the common complaints listed in a classic text (MacBryde CM, Blacklow RS, 1970):

- Pain
- Gastro-intestinal complaints
- Feverishness
- Cough
- Breathlessness
- Faints or fits
- Insomnia
- Anxiety
- Dizziness
- Palpitations
- Weakness
- Loss of vision
- Impaired hearing
- Bleeding

The number of diseases considered in our first "proof of concept" iteration has been confined to:

A. the ten conditions most associated with in-hospital death (Kellett and Deane, 2007):
   - Infection
   - Heart failure
   - Myocardial infarction
   - Chronic obstructive lung disease
   - Cancer
   - Diabetes
   - Kidney disease
   - Stroke
   - Dementia

B. The commonest diagnoses in primary care (Finley CR et al, 2018):
   - Upper respiratory tract infection
   - Asthma
   - Otitis media
   - Tonsillitis
   - Urinary tract infection
   - Hypertension
   - Arthritis
   - Dyspepsia
   - Depression
   - Dermatitis
   - Tuberculosis

4.2 Creation of Repository of Schema.org and Health-lifesci Structured Data

We have started the creation of a repository of health information by exploiting the semantic information available in the World Wide Web and, in particular, that provided by *schema.org*[1], an initiative funded by some major Web players, that aims to create, maintain, and promote schemas for structured data on the Internet. For the present work, we consider the *health-lifesci* extension[2] that contains 80 types, 162 properties and 125 enumeration values related to the health/medical field.

We have performed an analysis of the *health-lifesci* elements using the data made available by the Web Data Commons initiative[3] (Meusel, 2014. The Web Data Commons contain all Microformat, Microdata and RDFa (Resource Description Framework in Attributes) data extracted from the open repository obtained by the Web Common Crawl[4]. The whole dataset contains about 2.5 billion pages and almost 1 billion pages contain structured data. The dataset consists of 44 billion RDF n-quads[5]. These are sequences of RDF terms in the form {s, p, o, u}, where {s, p, o} represents a statement about semantic data consisting of subject, predicate, object, and {u} represents the Uniform Resource Identifier (URI) of the document from which the statement has been extracted.

From the whole dataset, we have extracted the subset containing *health-lifesci.schema.org* elements and the *schema.org* elements associated with each URI that contains *health-lifesci.schema.org* elements.

Since the queries (direct or indirect) from the users are about complaints and diseases, we have initially identified the corresponding *health-lifesci.schema.org* types (with the corresponding explanation). For what concerns the complaints, we have selected the *MedicalSignOrSymptom*[6] type. For what concerns the diseases, we have selected the *MedicalCondition*[7] type. Moreover, according to the user query and tailoring data, defined in Section 3, we have selected the following properties and types (explanations are taken from *health-lifesci.schema.org*):

- *name*, i.e., the name of the item.

[1] https://schema.org/
[2] https://health-lifesci.schema.org/
[3] http://webdatacommons.org/
[4] http://commoncrawl.org
[5] https://www.w3.org/TR/n-quads/
[6] https://schema.org/MedicalSignOrSymptom
[7] https://schema.org/MedicalCondition

- *description,* i.e., a description of the sign, symptom, or condition.
- *signOrSymptom*, i.e., a sign or symptom of the condition.
- *MedicalCause*, i.e., the causative agent(s) that are responsible for the pathophysiologic process that eventually results in a medical sign, symptom, or condition.
- *possibleTreatment*, i.e., a possible treatment.
- *drug*, i.e., a drug or medicine used in the treatment.
- *expectedPrognosis*, i.e., the likely outcome in either the short term or long term of the medical condition.
- *stage*, i.e., the stage of the condition, if applicable. It is used in the course of the disease.
- *epidemiology*, i.e., the characteristics of associated patients, such as age, gender, race, etc. They are used for tailoring the information.
- *riskFactor*, i.e., a modifiable or non-modifiable factor that increases the risk of a patient contracting this condition, e.g., age, coexisting condition. It is used for tailoring the information.
- *code*, i.e., a medical code for the entity, taken from a controlled vocabulary or ontology such as ICD-9, DiseasesDB, MeSH, SNOMED-CT, etc. It is used for connecting the *schema.org* data to other vocabularies such as the ones related to the Unified Medical Language System (UMLS)[8].

The *health-lifesci.schema.org* types and properties allow us to provide users with complete information about both complaints and diseases. In terms of tailoring, the system is presently limited to the current and background health status. We are in the process of adding further tailoring data to our repository and in particular:

- Lifestyle information
- Dynamic health indicators
- Empowerment level
- Health and wellbeing needs

4.3 User Interfaces

Pilot interfaces have been developed that allow the user to insert his/her health information in a conversational way so that the system can create a profile to tailor the user's query (Fig. 2 and 3).

Once the user has inserted all the information, the *conversational agent* processes the data, applies a decision rule algorithm, using the tailoring data, and retrieves the proper content from the schema.org database (Fig. 4).

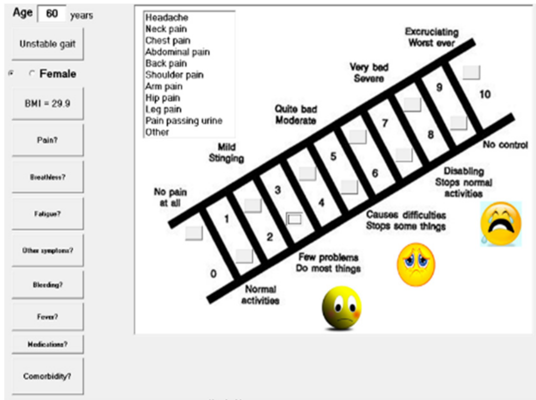

Figure 2: User interface for collecting current health status (e.g., complaint).

Figure 3: User interface for collecting background health status (e.g., gait information).

Element	Value	URL
Name	Sepsis	https://kcms-prod-mcorg.mayo.edu/diseases-conditions/sepsis/symptoms-causes/syc-20351214
Related Complaints	Fever	https://kcms-prod-mcorg.mayo.edu/diseases-conditions/sepsis/symptoms-causes/syc-20351214
Related Complaints	Breathing problem	https://kcms-prod-mcorg.mayo.edu/diseases-conditions/sepsis/symptoms-causes/syc-20351214
Related Complaints	Low blood pressure	https://kcms-prod-mcorg.mayo.edu/diseases-conditions/sepsis/symptoms-causes/syc-20351214
Related Complaints	Tachycardia	https://kcms-prod-mcorg.mayo.edu/diseases-conditions/sepsis/symptoms-causes/syc-20351214
Related Complaints	Low platelet count	https://kcms-prod-mcorg.mayo.edu/diseases-conditions/sepsis/symptoms-causes/syc-20351214
Code	SyS:SNOMED Code:91302008	https://kcms-prod-mcorg.mayo.edu/diseases-conditions/sepsis/symptoms-causes/syc-20351214
Code	SyS:SNOMED Code:238150007	https://kcms-prod-mcorg.mayo.edu/diseases-conditions/sepsis/symptoms-causes/syc-20351214

Figure 4: Preliminary output of the *conversational agent* for the *sepsis* disease.

Given that the present repository, as seen in Section 4.2, does not contain all the data that allow a complete tailoring of information, the *conversational agent* only uses the subset of information that allows such tailoring.

5 CONCLUSIONS

Our overall objective is that anyone anywhere, regardless of educational level or health literacy, will have instant access to health information they

[8] https://www.nlm.nih.gov/research/umls/index.html

understand, which will empower them to decide the wisest interventions, if any, for their immediate and future wellbeing. In this paper, we presented the principles and preliminary implementation of a conversational agent for patient empowerment that allows the user to specify his or her requests (either explicitly or implicitly) in terms of complaints and diseases and receives tailored health results for his or her understanding and empowerment.

To our best knowledge, this is the first attempt to create a conversational agent for patient empowerment (with a specific focus on comprehension) for general complaints and diseases. Moreover, the system is making a novel effort to mix data that come from different fields and are usually used separately. We are at the initial stage of the implementation phase and in the process of completing the health information repository by using other sources (such as the UMLS) and adding further tailoring data. We are also implementing the machine learning and selection mechanism that will provide the user with high-quality tailored information in a language that the user can easily understand. We are also implementing the quality/accuracy mechanism for the provided information (Alfano et al. 2020b). We plan to simulate different user typologies to test the system in all its different aspects and then run some tests with real users to evaluate its efficacy and fine-tune it.

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