Augmenting Guideline-Based CDSS with Experts' Knowledge

Nekane Larburu[1,2], Naiara Muro[1,2], Iván Macía[1,2], Eider Sánchez[3], Hui Wang[4], John Winder[5], Jacques Boaud[6,7] and Brigitte Séroussi[7,8]

[1]*eHeatlh and Biomedical Applications, Vicomtech-IK4, Donostia-San Sebastian, Spain*
[2]*Biodonostia, Donostia-San Sebastian, Spain*
[3]*NARU, Donostia-San Sebastian, Spain*
[4]*Computer Science Research Institute, Ulster University, Newtownabbey, United Kingdom*
[5]*Institute of Nursing and Health Research, Ulster University, Newtownabbey, United Kingdom*
[6]*AP-HP, DRCD, Paris, France*
[7]*Sorbonne Universités, UPMC Univ Paris 06, INSERM, Université Paris 13, Sorbonne Paris Cité, UMR S 1142, LIMICS, Paris, France*
[8]*AP-HP, Hôpital Tenon, DSP, Paris, France*
{nlarburu, nmuro, imacia}@vicomtech.org, e.sanchez@naruintelligence.com, h.wang@ulster.ac.uk, rj.winder@ulster.ac.uk, jacques.boaud@aphp.fr, brigitte.seroussi@aphp.fr

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Abstract: Over the past years, clinical guidelines have increasingly become part of the clinical daily practice in order to provide best available Evidence-Based-Medicine services. Hence, their formalization as computer interpretable guidelines (CIG) and their implementation in clinical decision support systems (CDSSs) are emerging to support clinicians in their decision making process and potentially improve medical outcomes. However, guideline compliancy in the clinical daily practice is still "low". Some of the reasons for such low compliance rate are (i) lack of a complete guideline to cover special clinical cases (e.g. oncogeriatric cases), (ii) absence of parameters that current guidelines do not consider (e.g. lifestyle) and (iii) absence of up-to-date guidelines due to lengthy validation procedures. In this paper we present a novel method to build a CDSS that, besides integrating CIGs, stores experts' knowledge to enrich the CDSS and provide best support to clinicians. The knowledge includes new evidence collected over time by the systematic usage of CDSSs.

1 INTRODUCTION

In order to offer the best available care, medical practice adopts the Evidence-Based-Medicine (EBM) principle, defined as *"the conscientious, explicit and judicious use of current best evidence in making decisions about care of individual patients"* (Sackett et al., 1996). In the 90s clinical practice guidelines (CPGs) start to appear as rigorous evaluations of different clinical activities that improved the clinical practice and developed health care processes (Grimshaw and Russell, 1994), so that clinicians could follow EBM. However, clinicians still found barriers to adhere to CPGs (Cabana MD et al., 1999). Some of these barriers were lack of awareness, lack of familiarity, lack of agreement, lack of outcome expectancy or the inertia to previous practice. These barriers are still valid in the current practice.

In order to overcome some of the main obstacles, during the last decade multiple CPGs have been formalized in an electronic way, i.e. computer interpretable guidelines (CIG), and applied in Clinical Decision Support Systems (CDSSs) (B. Séroussi et al., 2013). Nevertheless, it was discovered that CPGs still have limitations. For instance, in the context of breast cancer (BC) some factors such as elderly patients, multifocal tumours, occurrence of micrometastasis on lymph-node and patient choice are causes of CPGs non-compliance (Chéreau et al., 2011; Landercasper et al., 2006; Lebeau et al., 2011; B. Séroussi et al., 2013).

In this paper we present a method to acquire expert knowledge in order to develop a knowledge-augmented guideline-based CDSS. It results in the development of new tools to support clinicians on their decision making process for cases that have low evidence (e.g. oncogeriatric cases) or where other aspects (e.g. patient preferences) are crucial.

The rest of this paper is organized as follows. Section 2 presents the state of the art on CIG compliance. Section 3 presents the method to augment the guideline-based CDSS with expert´s knowledge. Section 4 presents the application of such method in an EU project, DESIREE, developed in the context of breast cancer. Section 5 proposed a short discussion on the presented method and Section 6 concludes the paper and gives some future work lines.

2 STATE OF THE ART

2.1 Guideline Compliance

Variations in medical practices have been observed for decades, questioning the quality of care (Mercuri and Gafni, 2011). CPGs compliance is one of the primary performance measures to assess the quality of medical practice. McGlynn et al. (McGlynn et al., 2003) reported that 54.9% of the studied patient population received CPGs' based recommended care, which vary from 10% to 78%. In their work they reported that for BC 75.7% were consistent with recommended care, based on 9 quality indicators. Other studies also demonstrated suboptimal guideline compliance levels in BC (Adegboyega et al., 2015; Landercasper et al., 2006; Lebeau et al., 2011; Wöckel et al., 2010). The published levels of guideline compliance range from 12% (Lebeau et al., 2011) to 100% (Adegboyega et al., 2015), depending on the definition of guideline compliance and the level of abstraction of the guideline. For instance, Wöckel et al. (Wöckel et al., 2010) reported 80% of adherence to German-S3-BC guideline for surgery and for hormone therapy, and 71% for chemotherapy, indicating different compliance levels for the different components of the care plan. Similarly, Lebeau et al. (Lebeau et al., 2011) reported high level of guideline compliance, but also said that "management of non-metastatic BC was fully compliant (considering jointly 20 quality criteria)".

2.2 Causes Associated with Guideline Non-Compliance

The causes of variations in care delivery are multifactorial. A review by Flottorp et al. (Flottorp et al., 2013) identified a list of 51 determinants of practice grouped in seven domains: guideline factors, individual health professional factors, patient factors, professional interactions, incentives and resources, capacity for organisational change, and social, political, and legal factors.

However, effective guideline-based CDSSs (Beeler et al., 2014; Roshanov et al., 2013) provide a framework for logging non-compliance cases and learn from them. As demonstrated by Séroussi et al. (B. Séroussi et al., 2013), guideline compliance increases by using guideline-based CDSS. Additionally, Bouaud et al. (Bouaud and Séroussi, 2011) determined the main factors related with CPG non-compliance and reported the distribution of non-compliance causes. Here, we list these causes reported in (Bouaud and Séroussi, 2011):

- ***Patient preferences***: When patients receive more complete information about the benefits and risks of different treatment options, the patients made their own active, informed decisions (Leonard et al., 2011). This decision is influenced by their personal preferences.
- ***Evolution of medical knowledge***: CPG knowledge may not consider latest scientific publications and clinical essays, and hence, they may lag behind 'last' evidence (B. Séroussi et al., 2013). This may include that 'new' parameters are not being considered in the applied guidelines.
- ***Specific situations***: Rare situations that require specific clinical research are also a cause of non-compliance. For example, in BC scenarios shown in (Parks et al., 2012; Schnitt, 1998; B Séroussi et al., 2013), microinvasion, neadjuvant situations and oncogeriatry conditions are the main causes that lead into non-compliance situations.
- ***Medical choices***: One of the main cause of non-compliance is a medical decision that is prioritized over the guideline recommendation. For example, in (Bouaud and Séroussi, 2011), the study reported that BC multidisciplinary staff meetings' choice (i.e. breast units choice) is the main reason reported as the cause for CPG non-compliance.
- ***Others***: Finally, it may be other reasons that lead into CPG non-compliancy that do not belong to any of the previously reported causes.

Some studies provide tools to support clinicians in understanding the reasons of non-compliancy (Hussain et al., 2007). Others exploit the stored patient information to predict patient worsening and prevent potential emergencies (Colantonio et al., 2008). Yet, there is no evidence that all the information related to the whole decision making process (such as additional patient data, the decision criteria for giving a specific treatment and patient outcomes) is stored and exploited over time to enrich the CDSS and provide better decision support to decision makers in prospective cases.

3 METHOD TO AUGMENT GUIDELINE-BASED CDSS

Here we present a method that enables the exploitation of the implicit knowledge used in a decision making process. The method is presented in the following subsections: Section 3.1 presents the starting point, which applies the clinical guideline model, Section 3.2 presents the second stage, which describes the acquisition process of experts' knowledge and Section 3.3 presents how such experts' knowledge is exploited.

3.1 Clinical Guideline Model

As discussed in Section 1, CPGs are intended to optimize patient care. Therefore, in this initial stage a clinical guideline model is developed. The clinical guideline model incorporates (i) different guidelines based on users' needs, (ii) updated clinical guidelines or studies, so that the provided recommendations correspond to the latest available evidence, and detects (iii) potential inconsistencies that could be reflected on the implemented guidelines.

3.2 Experts' Knowledge Acquisition

The second stage of this method focuses on experts' knowledge acquisition and storage.

We developed a flexible solution that enables the storage of each decisional event (Figure 1). Each **decisional event** reflects all the rationality for taking a decision and the consequences of such decision.

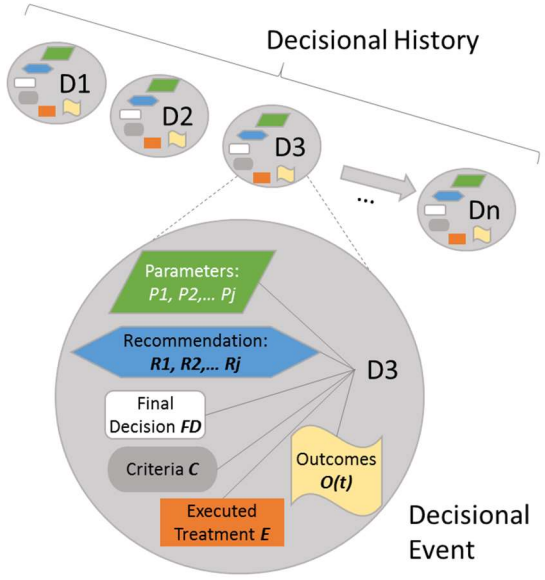

Figure 1: Decisional event and decisional history.

Hence, we define the decisional event as $\boldsymbol{D_n} = < \boldsymbol{P_i}, \boldsymbol{R_j}\ \boldsymbol{FD}, \boldsymbol{C_k}, \boldsymbol{E}, \boldsymbol{O(t)} >$, where (i) $\boldsymbol{P_i}$ is a set of patient *parameters* involved in the decision-making process, (ii) $\boldsymbol{R_j}$ is a set of clinical conditions (e.g. rules) wherein such parameters have been analysed, which results in a set of *recommendations* (iii) $\boldsymbol{FD}$ is a *final decision* that is taken by the decision maker, (iv) $\boldsymbol{C_k}$ is a set of *criteria* for which the final decision is made (which could be a patient parameter), (v) $\boldsymbol{E}$ is the executed treatment (usually, same as the final decision) and (vi) $\boldsymbol{O(t)}$ is the *health outcomes* of a patient measured over time t (e.g. ("ICHOM – International Consortium for Health Outcomes Measurement," n.d.)).

As shown in Figure 1, the storage of decisional events over time lead into a **decisional history**. The decisional history is later used to retrieve conclusions or discover new knowledge (Section 3.3).

3.3 Experts Knowledge Exploitation

Here we present the three usages of this decisional history: (i) recommendations assessment, (ii) patient similarity based recommendations and (iii) knowledge discovery to extend the knowledge base.

3.3.1 Recommendation Assessment

As presented by (Fox et al., 2009), "the current guideline development lifecycle does not provide appropriate tools to assess their impact on clinical practice". The proposed system is able to evaluate the decisions taken quantitatively (e.g. based on the number of times the recommendation was followed) and qualitatively (e.g. based on the patient outcomes – when the results are successful or match the defined decision criteria). This quantitative and qualitative measurements are presented to clinicians during the clinical decision making process to provide enriched information of the given recommendations.

3.3.2 Patients' Similarities

The system also applies similarity features between different patients and their results to support clinicians in their decision making process. For that, the system uses different metrics to determine which (clinical) parameters have higher impact when determining how similar a patient could be to a retrospective patient (e.g. age range, TNM classification etc.). In cases where the benefits and harms of a specific treatment are not clear, clinicians are able to consult previous similar patient cases and their outcome before taking a decision. The previous patient cases could be specific patient cases, or 'model' cases that summarise *n* past cases.

3.3.3 Knowledge Discovery

The experience acquired from the decisional history may enable different type of knowledge acquisition. Here we present the two types of knowledge considered in our research.

Firstly, the information from a large number of cases enables the **adjustment** of CPGs and protocols´ clinical conditions, e.g. in a form of a rule. For that, the scope of the criteria is redefined based on the cases where the given guideline-based recommendation is being followed with successful results. This is implemented using machine learning techniques. For example, if a decision criterion is parameter $a \in [0.5, 1.5]$, after applying machine learning techniques the system recognizes that the recommendation is being successful only when $a \in [0.8, 1.3]$. It also detects when a parameter, not previously included into the clinical condition for the decision making process, is determinant and should be part of the existing decision rule.

Secondly, large number of non-compliant cases with good or better results than the ones that follows the CPGs may lead into an **extension** of the CPGs´ clinical conditions (e.g. rules) by generating 'new' branches. This 'new' branches may include recommendations (treatment actions) that are not considered in the available CPGs (e.g. "clinical trial") or may include recommendations that are in the CPGs, but that are not considered for the given case.

This cases could make the knowledge base either more restrictive when a rule becomes more precise, but also could extend it with further procedures that were not included in the knowledge base.

In both adjustment and extension cases, in order to include the 'new' knowledge into the CDSS, the system verifies if the outcomes are positives and informs clinicians about its potential usage. If approved, this knowledge is included into the knowledge base for the CDSS (Figure 2). Nevertheless, the system provides the information of the recommendation source. This way clinicians are aware if the recommendation is guideline based or created automatically by the system based on the recorded experience or patient similarity properties.

4 DESIGN IN DESIREE

This study is being performed in the context of a European H2020 project, named DESIREE. In this section we present DESIREE project (Section 4.1) and the data flow diagram that represents our methodology within DESIREE (Section 4.2).

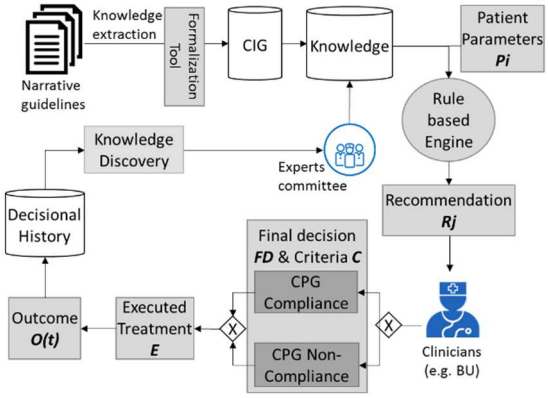

Figure 2: Data flow diagram.

4.1 DESIREE

DESIREE aims to provide decision support on the available therapy options by incorporating evidence based guidelines and experience from previous cases and outcomes. Hence, DESIREE goes beyond the limitations of existing guideline-based decision support systems. Such a system targets breast cancer (BC) cases, which is one of the most common and most deadly type of cancer affecting woman in the EU countries, with more than 460,000 new cases and 130,000 deaths in 2012 (Ferlay et al., 2013).

The users of such system are medical domain experts involved on breast units (BU) where patients' diagnosis and treatment decisions are taken. Hence, the system goal is to support BU during their weekly meetings in their multidisciplinary decision making process by providing not only CPGs based decision support, but also additional information extracted from previous cases over time.

4.2 DESIREE

The data flow diagram presented in Figure 2 is a high level representation of DESIREE platform. Since DESIREE is developed in the context of BC, in the depicted figure, Breast Units (BU) are the clinical experts that make the final decision. Here, we describe each block presented in Figure 2, omitting the blocks that correspond to the data presented in Section 3.2.

- ***Narrative Guidelines:*** In our methodological approach, the starting point is the analysis of representative and narrative CPGs used in BC care.
- ***Computer Interpretable Guidelines:*** Knowledge engineers extract the relevant information from CPGs and formalize it in a CIG. This covers the recommendations given

by guidelines for primary BC in several stages of the whole treatment till the patient is discharged. Hence, the CIG consider the previous treatments and the outcomes of them for the coming decision making action.

- ***Knowledge:*** The knowledge database stores knowledge from the CIG or from the decisional history exploitation´s "new" knowledge.
- ***Rule-based Engine:*** The rule-based engine is able to generate recommendations having as input the structured knowledge. Then, if patient data fulfils the clinical condition, the rules are fired and the engine generates one or more recommendations.
- ***Knowledge Discovery:*** Based on a large set of information stored in the decisional history, the system is capable of retrieving knowledge as discussed in Section 3.3.

5 DISCUSSION

The presented method overcomes some limitations of current guideline-based CDSS by providing enriched recommendations and additional information to clinicians in order to support them best in their decision making process. For that, we develop a new information structure based on decisional events. A decisional event stores the whole set of information used in the decision making process, including the consequences of the final decision, such as patient´s outcomes (e.g. quality of life).

Here we present some of the potential benefits and limitations of the proposed method. Firstly, the system promotes the usage of CPGs. Additionally, it assess the impact of the guidelines on clinical practice (Section 3.3.1), which is one of the critical factors detected by (Fox et al., 2009). Secondly, the system flexibility enables the storage of additional valuable information, such as the decision criteria, that could be used to adjust or/and extend the clinical conditions of the given protocols and CPGs over time (Section 3.3.3). This way it helps overcoming some of the limitations of current CPGs presented in Section 2, such as the impact of specific situations. This diverges from the work done in other projects, such as MobiGuide (Larburu et al., 2015), where the guidelines are customized and made context-aware beforehand during the knowledge engineering phase, and not over time depending on previous cases. Neither we focus on the discovery of temporal rules from time-stamped data, like in (Sacchi et al., 2007). Our study aims to discover rules from previous cases tracking each case to assess the outcomes and considering further information often not taken into account in current CPGs, such as the implicit knowledge of clinicians. Finally, the presented method combines both the CPGs and the knowledge generated automatically by the system based on their experience, which overcomes the requirements expressed by clinicians in (Miranda-Mena et al., 2006): "clinicians want a system that combines the protocol (or CPG) and their proper knowledge to suggest treatments".

6 CONCLUSIONS & FUTURE WORK

The hypothesis of this research is that such approach is more useful for clinicians, which expect a dynamic system that not only considers available CPGs and protocols, but also a system that is able to learn from the stored information over time to provide enriched decision support system.

In future work we aim to present among others the following points: (i) the tools used to convert the information acquired by experience into knowledge to extend and adjust the CPGs and protocols; (ii) a digital patient model ontology used for the CDSS, and particularly for similarity purposes; (iii) the methodology to assess the recommendations applying different metrics (survival rate, overall well-being, physical functioning etc.); and (iv) the validation of the system in a representative number of patients and the results.

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