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## ► To cite this version:

Jean-Baptiste Lamy, Abdelmalek Mouazer, Karima Sedki, Sophie Dubois, Hector Falcoff. Adaptive questionnaires for facilitating patient data entry in clinical decision support systems: Methods and application to STOPP/START v2. 2024. hal-04725462

**HAL Id: hal-04725462**

**<https://hal.science/hal-04725462v1>**

Preprint submitted on 8 Oct 2024

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# Adaptive questionnaires for facilitating patient data entry in clinical decision support systems: Methods and application to STOPP/START v2

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## Abstract

Clinical decision support systems are software tools that help clinicians to make medical decisions. However, their acceptance by clinicians is usually rather low. A known problem is that they often require clinicians to manually enter lots of patient data, which is long and tedious. Existing solutions, such as the automatic data extraction from electronic health record, are not fully satisfying, because of low data quality and availability. In practice, many systems still include long questionnaire for data entry.

In this paper, we propose an original solution to simplify patient data entry, using an *adaptive* questionnaire, *i.e.* a questionnaire that evolves during user interaction, showing or hiding questions dynamically. Considering a rule-based decision support systems, we designed methods for translating the system's clinical rules into display rules that determine the items to show in the questionnaire, and methods for determining the optimal order of priority among the items in the questionnaire. We applied this approach to a decision support system implementing STOPP/START v2, a guideline for managing polypharmacy. We show that it permits reducing by about two thirds the number of clinical conditions displayed in the questionnaire. Presented to clinicians during focus group sessions, the adaptive questionnaire was found "pretty easy to use". In the future, this approach could be applied to other guidelines, and adapted for data entry by patients.

**Keywords:** Adaptive questionnaire, Clinical decision support systems, Polypharmacy management, Medication review, Patient data entry, STOPP/START v2

## 1. Introduction

Clinical decision support systems (CDSS) [1] are software tools aimed at helping clinicians to make medical decisions, typically regarding diagnosis or therapy. Many CDSS have been proposed for chronic diseases [2], most of them implementing the paper clinical practice guidelines produced by learned societies. CDSS have the potential for improving healthcare. Meta-analysis [3, 4] showed that CDSS are effective at improving health care processes, despite their clinical and economic impacts are more difficult to assess.

However, clinicians acceptance with regard to CDSS is often rather low, and many reasons have been identified [5, 6, 7], including low computer literacy, low trust, reduction of professional autonomy, poor integration within the workflow, lack of time and the need for lots of patient data entry. Here, we will focus on the latter problem: for running the CDSS and obtaining recommendations, a clinician has to enter the clinical data of his/her patient, which is a tedious and time-consuming task. It has been shown that patient data entry contributes to physician burnout [8], but also that a lot of data entry can be associated with entry errors, leading to wrong decisions [9].

Several solutions have been proposed for helping with patient data entry. In particular, semantic interoperability [10] permits

the CDSS to reuse patient data previously entered elsewhere, typically in the electronic health record (EHR). For instance, in France, EHR exist and are usually based on the ICD terminology (International Classification of Diseases release 10). However, many patient conditions are still entered in EHR as free-text, and not coded using a medical terminology, impairing its reuse. This is especially true in primary care, where EHR are less structured and generalized than at hospital, and patient data is often spread over several EHR, owned by the GP and physicians of various medical specialties. Moreover, some CDSS may require data that is commonly not coded in EHR, either because it is too specific, or judged too trivial by the clinicians (*e.g.* all GPs do not enter an ICD10 code for "constipation"). Another option, natural language processing [11], allows the automatic coding of free-text, but almost never achieve a 100% accuracy. Finally, various physicians may use the same medical terminology in a different manner, resulting to different terms for the same patient [12]. To conclude, none of these solutions is perfect, and clinicians still have to check the patient data used by the CDSS and to enter the missing data, if any.

In practice, two approaches are commonly used for patient data entry in CDSS. The first approach consists of a list of patient conditions restricted to the conditions specifically relevant for the CDSS, associated with checkboxes. We used this approach in the past in the ASTI project [13] and in Vidal Reco using icons [14]. However, the list quickly becomes long as the number of parameters considered by the CDSS increases. The second approach consists of asking the clinicians to enter all patient conditions, *e.g.* using a terminology such as ICD10. But this is even more tedious.

In various domains, adaptive questionnaires have been used to facilitate data entry. An adaptive questionnaire is a questionnaire

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that evolves during user interaction, typically by showing or hiding questions, based on the previous answers given by the user.

The objective of this work is to propose an adaptive questionnaire for helping clinicians with patient data entry in rule-based CDSS. Since drug prescriptions are usually entered and coded in computerized physician order entry (CPOE), we will focus on the entry of patient clinical conditions. As a basic example, if a rule triggers if the patient has both hypertension and type 2 diabetes, an adaptive questionnaire may hide the “type 2 diabetes” question until the “hypertension” question is answered positively (or *vice versa*). Our approach consists of the automatic translation of the CDSS rule base into a set of rules that determine whether each patient condition is shown, and the heuristic ordering of patient conditions for finding the best priority order between them (*e.g.* should we ask for hypertension or for type 2 diabetes in the example above?). The approach also includes a dedicated user interface for the questionnaire.

This study takes place in the context of the ABiMed research project [15], aimed at designing a CDSS for managing polypharmacy that associates rule-based systems with advanced user interfaces. Many CDSS have been proposed in that domain [16, 17, 18], most of them being based on the implementation of guidelines using patient data manually entered by clinicians or extracted from EHR. We applied the proposed adaptive questionnaire approach to STOPP/START v2 [19], a guideline for patients with polypharmacy, *i.e.* consuming five drugs or more. This guideline is commonly used for performing medication reviews [20], which are structured patient interviews carried out by the pharmacist with the aim of optimizing patient care. In that context, EHR data extraction is very difficult to consider, because community pharmacists do not have access to the GP or hospital EHR. In the ABiMed project, we aim at extracting data from the GP’s EHR and sending it to the pharmacist, however, in France, GP EHR are fragmented over various editors and formats, and we currently work with a single editor. For GPs using EHR from another editor, or for verification purpose, it is very important to propose an optimized user interface for manual data entry for pharmacists. We evaluated the proposed system in terms of the number of patient conditions asked, and clinicians opinion during focus group sessions.

The rest of the paper is organized as follows. Section 2 describes related works on adaptive questionnaires. Section 3 describes the methods used for designing the adaptive questionnaire and the associated user interface, and its application to STOPP/START v2. Section 4 presents the adaptive questionnaire user interface and the results of the evaluations. Section 5 discusses the methods and the results, and, finally, section 6 concludes.

## 2. Related works

Adaptive questionnaires should be distinguished from *dynamic forms*. A dynamic form is a questionnaire that is dynamically generated from a knowledge source [21]. But contrary to an adaptive questionnaire, a dynamic form does not change during the user interaction. F Sadki *et al.* [22] proposed an example of dynamic forms, through a web application that generates a semantically structured web form from an ontology.

Various categories of adaptive questionnaires exist. An adaptive questionnaire can be *ordered*, when the questions must be answered in a given order and new questions only appear after the last question answered, or *unordered*, when questions can be answered in any order and new questions may appear anywhere in

the questionnaire (after or before the last answered question).

An adaptive questionnaire can be *exhaustive*, when all relevant questions are shown (*e.g.* pregnancy status is relevant for a female patient but not for a male patient), or *heuristic*, when only the most important questions are shown, the importance of the questions being evaluated with regards to their impact on the decision (*e.g.* pregnancy status may have a low impact on the decision for a particular female patient, and thus not shown).

Several ordered heuristic adaptive questionnaires were proposed for assessing learning style in education. E Mwamikazi *et al.* [23] proposed a system that classifies students in Myers-Briggs Type accurately while asking 81% less questions than state-of-the-art systems. The system relies on a question sorting algorithm that takes into account the discriminative power of the questions with regards to the Myers-Briggs Type class. A Ortigosa *et al.* [24] proposed AH-questionnaire, a system based on the C4.5 algorithm and decision trees, for reducing the number of questions asked for determining the Felder-Silverman’s Learning Style Model.

USHER [25] combines a dynamic form with an ordered heuristic adaptive questionnaire. The system learns a probabilistic model over the questions for ordering them. In addition, USHER can also re-ask questions that have a high probability of being associated with an erroneous answer.

ADAPQUEST [26] is a Java tool for the development of ordered heuristic adaptive questionnaires, based on Bayesian networks. The tool has been applied to the diagnosis of mental disorders.

Several systems have been proposed for helping patients to enter their medical data. DQueST [27] proposes an unordered heuristic adaptive questionnaire for helping patients to find clinical trials for which they are eligible. The system starts like a free-text search, as usual search engines. Then, it ranks questions and identify the most informative ones. The approach is unordered, the user being able to choose what type of question he/she will answer next (*e.g.* a question on diagnosis or prescribed treatment). RC Gibson *et al.* [28] proposed an ontology-based ordered exhaustive adaptive questionnaire in order to help patients with learning disabilities to report their symptoms. The questionnaire adapts itself according to the patient answer, but also according to his/her disabilities. X Kortum *et al.* [29] proposed an ordered heuristic adaptive questionnaire for self-diagnosis. The authors rely on machine learning for selecting and ordering questions. PC Sherimon *et al.* [30] proposed an ordered exhaustive adaptive questionnaire for helping patients to enter medical data. The system is associated with a CDSS for diabetes.

Chronic-pharma [31] includes the LESS-CHRON module, aimed at helping to deprescribe drugs. It proposes an ordered exhaustive adaptive questionnaire for entering patient drug order and main conditions. The questionnaire is structured on three levels: first, the clinician select the anatomic groups of the drugs taken by the patient (*e.g.* cardiovascular), then the drug classes (*e.g.* antihypertensives), and finally the prescription characteristics (*e.g.* treatment duration) and relevant patient conditions (*e.g.* systolic blood pressure <160 mmHg). At levels 2 and 3, only the items corresponding to the items selected at the previous level are shown.

## 3. Methods

In this work, we opted for an *unordered exhaustive* adaptive questionnaire. Exhaustive, because all relevant questions have to be asked in a guideline-based CDSS. And unordered, because

clinicians usually expect questions relative to patient conditions to be organized by anatomic groups, rather than being ordered by importance.

### 3.1. Clinical rule formalization

Let us consider  $C = \{C_1, C_2, \dots, C_n\}$ , a set of  $n$  clinical conditions,  $D = \{D_1, D_2, \dots\}$ , a set of non-clinical conditions (e.g. prescribed drugs), and  $R = \{R_1, R_2, \dots, R_m\}$ , a set of  $m$  clinical rules of the following form:

$$\begin{aligned} & C_1^p \wedge C_2^p \wedge \dots \wedge D_1^p \wedge D_2^p \wedge \dots \\ \wedge & \neg C_1^a \wedge \neg C_2^a \wedge \dots \wedge \neg D_1^a \wedge \neg D_2^a \wedge \dots \\ \wedge & (C_1^{u1} \vee C_2^{u1} \vee \dots \vee D_1^{u1} \vee D_2^{u1} \vee \dots) \\ \wedge & (C_1^{u2} \vee C_2^{u2} \vee \dots \vee D_1^{u2} \vee D_2^{u2} \vee \dots) \wedge \dots \rightarrow A \end{aligned}$$

where  $C^p = \{C_1^p, C_2^p, \dots\}$  and  $D^p = \{D_1^p, D_2^p, \dots\}$  are the clinical and non-clinical conditions that must be present in the patient for triggering the rule, respectively,  $C^a = \{C_1^a, C_2^a, \dots\}$  and  $D^a = \{D_1^a, D_2^a, \dots\}$  are the clinical and non-clinical conditions that must be absent,  $C^{u1} = \{C_1^{u1}, C_2^{u1}, \dots\}$  and  $D^{u1} = \{D_1^{u1}, D_2^{u1}, \dots\}$  are the clinical and non-clinical conditions that are members of the first union in the rule,  $C^{u2}$  and  $D^{u2}$  are those of the second union, etc., and  $A$  is the action triggered by the rule (e.g. prescribing a given drug; actions are not detailed here for the sake of simplicity). These rules can also be written:

$$\begin{aligned} & \bigwedge \{c \in C^p\} \\ \wedge & \bigwedge \{d \in D^p\} \\ \wedge & \bigwedge \{\neg c \in C^a\} \\ \wedge & \bigwedge \{\neg d \in D^a\} \\ \wedge & \bigwedge_{z=1}^{|U|} (\bigvee \{c \in C^{uz}\} \vee \bigvee \{d \in D^{uz}\}) \rightarrow A \end{aligned}$$

A clinical rule  $R_i$  of that form can be formalized as a 6-element tuple  $R_i = (C^p, D^p, C^a, D^a, U = \{(C^{u1}, D^{u1}), (C^{u2}, D^{u2}), \dots\}, A)$  where the first four elements are the sets of present and absent clinical and non-clinical conditions, the fifth element  $U$  is the set of the unions in the rule, each union being formalized as a pair of clinical and non-clinical conditions, and the sixth element is the action  $A$ .

For example, here are two clinical rules from STOPP/START:

- START rule D2: "Start fibre supplements (e.g. bran, ispaghula, methylcellulose, sterculia) for diverticulosis with a history of constipation".

- STOP rule D6: "Stop antipsychotics (i.e. other than quetiapine or clozapine) in those with parkinsonism or Lewy Body Disease (risk of severe extra-pyramidal symptoms)".

They can be formalized as follows:

$$R_{D2} = \text{constipation} \wedge \text{diverticulosis} \wedge \neg \text{fibre} \rightarrow \text{start}(\text{fibre})$$

$$= \left( \begin{array}{l} C^p = \{\text{constipation, diverticulosis}\} \\ D^p = \emptyset \\ C^a = \emptyset \\ D^a = \{\text{fibre}\} \\ U = \emptyset \\ A = \text{start}(\text{fibre}) \end{array} \right)$$

$$R_{D6} = \text{antipsychotics} \wedge (\text{parkinsonism} \vee \text{Lewy Body}) \rightarrow \text{stop}(\text{antipsychotics})$$

$$= \left( \begin{array}{l} C^p = \emptyset \\ D^p = \{\text{antipsychotic}\} \\ C^a = \emptyset \\ D^a = \emptyset \\ U = \{(\{\text{parkinsonism, Lewy Body}\}, \emptyset)\} \\ A = \text{stop}(\text{antipsychotic}) \end{array} \right)$$

### 3.2. Display rule generation

We call *display rule* a rule that determines whether a given clinical condition  $x$  should be displayed and asked for manual entry

by a clinician. Display rules are distinct from clinical rules, aiming at diagnosis or therapy. The action of a display rule is the display of a given clinical condition in the form. The set of conditions that should be displayed in the form can be obtained by executing all display rules and showing conditions for which at least one display rule states that it should be displayed. When the patient profile changes (e.g. a new drug is prescribed, or a clinical condition has been entered), display rules must be executed again to determine the clinical conditions to display after the change.

In the design of the algorithm for generating display rules, we made the following assumptions: (a) It is preferable to display the lowest possible number of clinical conditions, in order to simplify the questionnaire and reduce the time required for data entry. (b) Non-clinical conditions (e.g. drug prescriptions or lab test results) are already known and coded (otherwise, they should be treated as clinical conditions in the following formula), and thus they will be checked first. (c) Clinical conditions are more likely to be false than true (this is verified for almost all conditions, with the possible exception of hypertension and renal failure for the elderly). Thus, clinical conditions that must be present will be displayed before those that must be absent.

Consequently, in display rules, the conditions will be considered in the following order of priority: first, check the  $D^p$  and  $D^a$  member of the rule 6-element tuple, then check  $C^a$ , finally check  $C^p$  and  $U$ . For example, for  $R_{D2}$ , display rules will first check that fibre is absent ( $D^a$ ), then display the first clinical condition (constipation or diverticulosis,  $C^p$ ), and display the second one only if the first one is true. Whether constipation or diverticulosis is shown first is here an arbitrary choice, thus we have to define an order of priority between clinical conditions.

Let us consider a strict total order  $<$  between the clinical conditions in  $C$ , such that  $c1 < c2$  means that  $c1$  is displayed preferably than  $c2$  when one of them must be chosen to be displayed first (e.g. if a rule has for conditions  $c1 \wedge c2$ , and if  $c1 < c2$ , then  $c1$  is displayed, and  $c2$  will be displayed only if  $c1$  is present). We will explain later how to find the best order  $<$ . For each clinical condition  $x \in C^p$  in rule  $R_i$ , we define the rule  $\mathcal{R}^p(R_i, x)$  that determines whether present clinical condition  $x \in C^p$  needs to be displayed, or not, as follows:

$$\begin{aligned} \mathcal{R}^p(R_i, x \in C^p) &= \bigwedge \{c \in C^p \mid c < x\} \\ &\wedge \bigwedge \{d \in D^p\} \\ &\wedge \bigwedge \{\neg c \in C^a\} \\ &\wedge \bigwedge \{\neg d \in D^a\} \\ &\wedge \bigwedge_{z=1}^{|U|} \left\{ \begin{array}{l} \bigvee \{c \in C^{uz}\} \vee \bigvee \{d \in D^{uz}\} \\ \text{if } \forall c \in C^{uz}, c < x \\ \text{True otherwise} \end{array} \right. \\ &\rightarrow \text{display}(x) \end{aligned}$$

$\mathcal{R}^p$  displays the condition  $x$  if non-clinical conditions are satisfied ( $D^p$  and  $D^a$ ), absent clinical conditions are satisfied ( $C^a$ ), and present clinical conditions in  $C^p$  and  $U$  that have priority on  $x$  are satisfied.

We define two rule  $\mathcal{R}^{a1}(R_i, x \in C^a)$  and  $\mathcal{R}^{a2}(R_i, x \in C^a)$  for each clinical condition that must be absent:

$$\begin{aligned} \mathcal{R}^{a1}(R_i, x \in C^a) &= \bigwedge \{c \in C^p\} \\ &\wedge \bigwedge \{d \in D^p\} \\ &\wedge \bigwedge \{\neg c \in C^a \mid c \neq x\} \\ &\wedge \bigwedge \{\neg d \in D^a\} \\ &\wedge \bigwedge_{z=1}^{|U|} (\bigvee \{c \in C^{uz}\} \vee \bigvee \{d \in D^{uz}\}) \\ &\rightarrow \text{display}(x) \end{aligned}$$

$$\begin{aligned}
\mathcal{R}^{a2}(R_i, x \in C^a) &= \{x\} \\
&\wedge \bigwedge \{d \in D^p\} \\
&\wedge \bigwedge \{\neg c \in C^a \mid c < x\} \\
&\wedge \bigwedge \{\neg d \in D^a\} \\
&\rightarrow \text{display}(x)
\end{aligned}$$

Since clinical conditions are expected to be more frequently false than true, absent conditions are checked lastly.  $\mathcal{R}^{a1}$  displays the condition  $x$  if all other conditions are satisfied (*i.e.* non-clinical conditions  $D^p$  and  $D^a$ , present clinical conditions  $C^p$ , unions  $U$  and other absent clinical conditions in  $C^a$ ).  $\mathcal{R}^{a2}$  displays the condition  $x$  if it is true and if other conditions that have priority are satisfied.  $\mathcal{R}^{a2}$  is needed to permit the user to remove condition  $x$  if it has been set, but the other conditions of the rules have not been set. This normally cannot occur when interacting with the system starting from an empty list of clinical conditions; however, it may occur if the initial list of clinical conditions is not empty (*e.g.* if some clinical conditions are automatically extracted from EHR, and then the clinician verifies them and completes them is needed).

Finally, we define two rules  $\mathcal{R}^{u1}(R_i, x \in C^{uk})$  and  $\mathcal{R}^{u2}(R_i, x \in C^{uk})$  for each clinical condition that is a member of a union, with  $1 \leq k \leq |U|$ .

$$\begin{aligned}
\mathcal{R}^{u1}(R_i, x \in C^{uk}) &= \bigwedge \{c \in C^p \mid c < x\} \\
&\wedge \bigwedge \{d \in D^p\} \\
&\wedge \bigwedge \{\neg c \in C^a\} \\
&\wedge \bigwedge \{\neg d \in D^a\} \\
&\wedge \bigwedge_{z=1}^{|U|} \begin{cases} \bigwedge \{\neg c \in C^{uz}\} \wedge \bigwedge \{\neg d \in D^{uz}\} \\ \text{if } x \in C^{uz} \\ \bigvee \{c \in C^{uz}\} \vee \bigvee \{d \in D^{uz}\} \\ \text{if } \forall c \in C^{uz}, c < x \\ \text{True otherwise} \end{cases} \\
&\rightarrow \text{display}(x)
\end{aligned}$$

$$\begin{aligned}
\mathcal{R}^{u2}(R_i, x \in C^{uk}) &= \bigwedge \{c \in C^p \mid c < x\} \\
&\wedge \bigwedge \{d \in D^p\} \\
&\wedge \bigwedge \{\neg c \in C^a\} \\
&\wedge \bigwedge \{\neg d \in D^a\} \\
&\wedge \bigwedge_{z=1}^{|U|} \begin{cases} \{x\} \text{ if } x \in C^{uz} \\ \bigvee \{c \in C^{uz}\} \vee \bigvee \{d \in D^{uz}\} \\ \text{if } \forall c \in C^{uz}, c < x \\ \text{True otherwise} \end{cases} \\
&\rightarrow \text{display}(x)
\end{aligned}$$

$\mathcal{R}^{u1}$  displays the condition  $x$  if no condition in the union is true and if other conditions that have priority are satisfied.  $\mathcal{R}^{u2}$  displays the condition  $x$  if it true and if other conditions that have priority are satisfied. Similarly to  $\mathcal{R}^{a2}$ ,  $\mathcal{R}^{u2}$  is only needed to permit the clinician to unset the condition  $x$  if it was set outside of the questionnaire.

Notice that display rules can be expressed as 6-element tuples, exactly as clinical rules. Considering  $R_i = (C^p, D^p, C^a, D^a, U, A)$ , we have:

$$\mathcal{R}^p(R_i, x \in C^p) = \left( \begin{array}{l} \{c \in C^p \mid c < x\} \\ D^p \\ C^a \\ D^a \\ \{(C^u, D^u) \in U \mid \forall c \in C^u, c < x\} \\ \text{display}(x) \end{array} \right)$$

$$\mathcal{R}^{a1}(R_i, x \in C^a) = \left( \begin{array}{l} C^p \\ D^p \\ C^a \setminus \{x\} \\ D^a \\ U \\ \text{display}(x) \end{array} \right)$$

$$\mathcal{R}^{a2}(R_i, x \in C^a) = \left( \begin{array}{l} \{x\} \\ D^p \\ \{c \in C^a \mid c < x\} \\ D^a \\ \emptyset \\ \text{display}(x) \end{array} \right)$$

$$\mathcal{R}^{u1}(R_i, x \in C^{uk}) = \left( \begin{array}{l} \{c \in C^p \mid c < x\} \\ D^p \\ C^a \cup C^{uk} \\ D^a \cup D^{uk} \\ \{(C^u, D^u) \in U \mid C^u \neq C^{uk} \wedge \forall c \in C^u, c < x\} \\ \text{display}(x) \end{array} \right)$$

$$\mathcal{R}^{u2}(R_i, x \in C^{uk}) = \left( \begin{array}{l} \{c \in C^p \mid c < x\} \cup \{x\} \\ D^p \\ C^a \\ D^a \\ \{(C^u, D^u) \in U \mid C^u \neq C^{uk} \wedge \forall c \in C^u, c < x\} \\ \text{display}(x) \end{array} \right)$$

We denote by  $R^d$  the set of all display rules generated from the clinical rules in  $R$ .

For example, for START rule D2 and STOP rule D6, and considering *constipation* < *diverticulosis*, we obtain the following display rules:

$$\begin{aligned}
\mathcal{R}^p(R_{D2}, \text{constipation}) &= \neg \text{fibre} \\
&\rightarrow \text{display}(\text{constipation}) \\
\mathcal{R}^p(R_{D2}, \text{diverticulosis}) &= \text{constipation} \wedge \neg \text{fibre} \\
&\rightarrow \text{display}(\text{diverticulosis})
\end{aligned}$$

$$\begin{aligned}
\mathcal{R}^{u1}(R_{D6}, \text{parkinsonism}) &= \text{antipsychotics} \wedge \neg \text{Lewy Body} \\
&\rightarrow \text{display}(\text{parkinsonism})
\end{aligned}$$

$$\begin{aligned}
\mathcal{R}^{u2}(R_{D6}, \text{parkinsonism}) &= \text{antipsychotics} \wedge \text{parkinsonism} \\
&\rightarrow \text{display}(\text{parkinsonism})
\end{aligned}$$

$$\begin{aligned}
\mathcal{R}^{u1}(R_{D6}, \text{Lewy Body}) &= \text{antipsychotics} \wedge \neg \text{parkinsonism} \\
&\rightarrow \text{display}(\text{Lewy Body})
\end{aligned}$$

$$\begin{aligned}
\mathcal{R}^{u2}(R_{D6}, \text{Lewy Body}) &= \text{antipsychotics} \wedge \text{Lewy Body} \\
&\rightarrow \text{display}(\text{Lewy Body})
\end{aligned}$$

For START rule D2, if fibre is already prescribed, no clinical condition is displayed. Otherwise, only constipation is displayed. When constipation is checked, diverticulosis is displayed.

### 3.3. Formalization of the ordering problem

Identifying the best global strategy for asking clinical conditions can be formalized as an ordering problem: finding the optimal strict total order < between the clinical conditions in  $C$  that minimizes the number of distinct clinical conditions displayed in the questionnaire when no clinical condition are entered yet, *i.e.* finding < that minimizes:

$$\left\{ \left\{ x \in C \mid \exists R_j^d \in R^d \text{ such as } R_j^d = \text{conditions} \rightarrow \text{display}(x) \text{ and conditions are satisfied} \right\} \right\}$$

### 3.4. Proof of NP-hardness

The ordering problem can be proved to be NP-hard, by reducing it to the Generalized Traveling Salesman Problem (GTSP). The Traveling Salesman Problem (TSP) consists in finding the shortest travel that passes through a given set of towns. The GTSP is similar, but also considers a set of areas, each town being located

in a given area, and the travel must pass through one town of each area (instead of all towns). Both TSP and GTSP are NP-hard.

For the sake of simplicity, we will restrict the proof to simpler display rules of the form  $R' = \bigwedge \{c \in C^p\} \rightarrow A = (C^p, \emptyset, \emptyset, \emptyset, A)$ , and we will consider that all patient conditions are false. With such rules, the order  $<$  can be built progressively, from left to right. An order  $<$  under construction is of the form  $C_a < C_b < \dots < C_\alpha \simeq C_\beta \simeq \dots$ . In such order, conditions  $C_{ord} = \{C_a, C_b, \dots\}$  have been ordered and other conditions  $C_{unord} = \{C_\alpha, C_\beta, \dots\}$  have not yet been ordered, with  $\forall c \in C_{ord} \forall c' \in C_{unord}, c < c'$ . In the definition of  $\mathcal{R}^p(R_i, x)$ , if we consider a rule of the form  $R'$ , we can see that it will generate display rules of the form:  $True \rightarrow display(C_a), C_a \rightarrow display(C_b), C_a \wedge C_b \rightarrow display(C_c), \dots$  for the order  $C_a < C_b < C_c < \dots$ . If we assume that, in the initial form, all clinical conditions are false, the display rules  $\mathcal{R}^p(R_i, x)$  will lead to the display of a single condition, the first one according to the order  $<$  in  $C^p$ . Let us note  $C_r^p$  the  $C^p$  component of the rule  $r$ . We search the order  $<$  that minimizes the number of clinical conditions displayed in the initial form, *i.e.*:

$$\left\{ x \mid \exists r \in R^d \text{ such that } x \in C_r^p \text{ and } \forall y \in C_r^p \text{ with } y \neq x, x < y \right\}$$

In the GTSP reformulation of the problem, the distance corresponds to the number of clinical conditions displayed in the form. We cannot represent each clinical condition by a town. In fact, in GTSP, when adding a new town in the travel, the cost (*i.e.* the distance) depends only on the current town and the new town added; on the contrary, in our problem, when adding a new clinical condition  $x$  to the right of the order  $<$ , the cost depends on all clinical conditions already present in the order  $<$  under construction, and not only on the last one. The cost of the addition is 1 (*i.e.*, one new condition to display in the form) if there is at least one rule that includes  $x$  in its conditions  $C^p$  and that includes no other condition already present in the order  $<$  under construction; otherwise it is 0 (no new condition to display).

Consequently, we considered a town as being the subset of the clinical conditions currently included in the order  $<$  under construction (*i.e.*  $C_{ord}$ ). Thus, the ordering problem can be rewritten as a GTSP by considering a set of  $2^n$  towns  $T = \{x \subseteq C\}$ , and a set of  $n+1$  areas  $A = \{A_0, A_1, \dots, A_n\}$ , each town  $t$  belonging to the area  $A_{|t|}$ , *i.e.*  $A_k = \{t \in T \mid |t| = k\}$ .

The optimal strict total order can be deduced by ordering the clinical conditions in their order of appearance in the town sets. For example, if the solution found is  $(\{\}, \{C_1\}, \{C_1, C_3\}, \{C_1, C_3, C_2\})$ , then the optimal total order is  $C_1 < C_3 < C_2$ .

The asymmetric distance matrix  $M$  of the GTSP is defined as follows:

$$M(i \in T, j \in T) = \begin{cases} 0 & \text{if } i \in A_n \wedge j \in A_0 \\ +\infty & \text{if } \neg(i \in A_k \wedge j \in A_{k+1}) \\ 1 & \exists r \in R \mid j \setminus i \subseteq C_r^p \wedge i \cap C_r^p = \emptyset \\ 0 & \text{otherwise} \end{cases}$$

The first condition gives a distance of 0 for closing the loop of the travel.

The second condition gives a distance of  $+\infty$  when the salesman travels from a town in the area  $A_k$  to a town that is not in area  $A_{k+1}$ , in order to force to visit all areas in order.

The third condition gives a distance of 1 if the salesman travels to a town that adds a new clinical condition that is present in a rule for which no other condition is already present in the departure town.

The distance is 0 otherwise.

### 3.5. Solving the ordering problem

NP-hard problems can only be solved by testing all possible solutions, or by using heuristic algorithms that give a good solution, but not necessarily the best one. In theory, the optimal clinical conditions order is patient-dependent: in particular, rules having non-clinical conditions only impact patients having these conditions.

We considered two options for solving the ordering problem: (1) a simple heuristic that sorts clinical conditions in decreasing order of their number of occurrences in the rules, producing a global, patient-independent, order, and (2) the Artificial Feeding Birds (AFB) metaheuristic [32], for computing a near optimal, patient-specific order.

### 3.6. User interface design

Each clinical condition is displayed as a checkbox in the user interface. Checkboxes are grouped in 13 general categories (*e.g.* cardiology, digestive system, *etc.*) to facilitate the search of a particular condition. We previously designed and used these 13 categories and their associated colors in a work focused on adverse drug events [33].

Some conditions are associated with several codes in the terminology, *e.g.* “diabetes” can be associated with ICD10 (International Classification of Diseases, 10<sup>th</sup> revision) codes E10 (insulin-dependent diabetes mellitus), E11 (non-insulin-dependent diabetes mellitus), *etc.* In that case, when the box is checked, a drop-down combo box allows the user to select the appropriate term. By default, the most general term is selected, *e.g.* E14 (unspecified diabetes mellitus).

In rare cases, a clinical condition may be more general than another one, *i.e.* related together with “is a” relation (*e.g.* “diabetes” is more general than “type 2 diabetes”). In that case, only the most general condition is displayed (*e.g.* “diabetes”), and the user may select the desired code in the drop-down combo box (including the code for the more specific condition).

When new conditions appear during user interaction, following the selection of a given condition, the new conditions are highlighted in yellow and marked with a red star.

### 3.7. Application to STOPP/START v2

STOPP/START v2 is a clinical guideline for medication reviews [19]. It includes 114 recommendations, with both recommendations for stopping current drug treatment (STOPP) and for starting new prescriptions (START).

Our implementation was written in Python 3 with the Owlready 2 ontology-oriented programming module [34] for Python. Clinical rules were expressed in a high-level language that is automatically translated into SPARQL queries. Clinical conditions were coded using ICD10. For more details on the implementation of STOPP/START, please refer to the coded algorithms proposed by CJA Huibers *et al.* [35] and our previous publication for the global architecture of the system [36].

### 3.8. Evaluation methods

In a first experiment, the proposed method was tested on 10 realistic clinical cases designed by a GP (HF). We evaluated both the number of clinical conditions displayed and the time required for executing the display rules. The method was executed on a modern laptop computer (processor: Intel Core i7-10510U CPU, 1.80 GHz).

In a second experiment, we organized focus group sessions for presenting ABiMed, our CDSS for medication reviews, to clinicians (both GPs and pharmacists). A prototype of our CDSS was

shown, various user interfaces focused on polypharmacy management were presented during the focus groups, including the proposed adaptive questionnaire and the implementation of the STOPP/START v2 guideline. Then, a clinical case was given and solved together, using the support of the CDSS. We asked the opinion of the clinicians, and in particular whether the fact that checkboxes may appear or disappear during the data entry would be disturbing, or not. Focus groups were tape-recorded and then transcribed.

## 4. Results

### 4.1. Application to STOPP/START v2

The proposed methods were applied to STOPP/START v2. Three recommendations were considered as too general for implementation (STOPP A1, A2 and A3). The other 111 recommendations were translated into 124 clinical rules (a few recommendations were split in two rules). The implementation of STOPP/START v2 considered a total of 73 distinct clinical conditions (55 for STOPP rules and 30 for START, 12 conditions belonging to both). Using the proposed methods, 197 display rules were generated (136 for STOPP rules and 61 for START).

### 4.2. User interface

Figure 1 shows the adaptive questionnaire we designed, for a patient having an empty drug order. There are 23 conditions displayed, grouped in anatomical categories. Each category is represented by a panel with a colored title bar, and each condition is represented by a checkbox. Panels are organized on 4 columns, in order to display all conditions on a single screen, without having to scroll up and down.

As a matter of comparison, supplementary file #1 shows the entire questionnaire, if it was not adaptive, thus displaying all clinical conditions.

Figure 2 shows the same questionnaire after the user checked the “diabetes with renal manifestation” condition. In addition to the check in the checkbox, the questionnaire was adapted on two points. First, a drop-down combo box is now displayed for choosing the appropriate ICD10 term (since there are several ICD10 terms that correspond to diabetes with renal manifestation). Second, a new condition, “proteinuria”, appeared on the right. This condition was not necessary for applying STOPP/START rules before checking “diabetes with renal manifestation”, but becomes necessary after. The new condition is temporarily highlighted with a yellow background, to attract user attention. It also has a red star after its label. The red star is more subtle than the yellow background, but remains permanently.

Similarly, conditions may disappear during user interaction, e.g. the “proteinuria” condition would disappear if the user unchecks the “diabetes with renal manifestation” condition.

### 4.3. Evaluation results

Table 1 shows the results obtained when applying the proposed methods to 10 realistic clinical cases of old patients with polypharmacy, using the simple heuristics described in the methods section for finding a global order of the clinical conditions. The execution time remains lower than 0.1 second on a modern computer, which is compatible with a clinical use. When using the AFB metaheuristic to compute a patient-specific clinical conditions order, the algorithm quickly converged, and we obtained exactly the same results in terms of the number of conditions displayed, but the execution time was longer (about 0.4 second). We thus keep the simple heuristic.

Out of the 73 clinical conditions required for STOPP/START v2, only 26.7 conditions are displayed on average, which is 36.6% (almost a two-third reduction). This represents an important reduction in the number of conditions to enter or review manually. More specifically, the reduction is much more important for STOP (only 15.6% of the conditions are displayed), than for START (66.3% of the conditions are displayed). This was expected, because all STOP recommendations have a drug condition that must be present (*i.e.*  $D^p \neq \emptyset$ ), thus allowing displaying the clinical conditions of the recommendation only if the drug is present. On the contrary, START recommendations may have no such drug condition. Nevertheless, we observe that the proposed method still substantially reduces the number of conditions displayed for START.

We organized two focus group sessions, with a total of 16 clinicians (8 GPs and 8 pharmacists). The first session was performed in a rural environment, with 4 pharmacists (2 males, 2 females) and 4 GPs (4 males). All clinicians were young (30-40 years old). Seven clinicians were young (30-40) and one was older (> 65). The second session was performed in a city environment, with 4 pharmacists (3 males, 1 females) and 4 GPs (2 males, 2 females). Four were young (30-40) and four were older (50-65).

Clinicians understood easily how the adaptive questionnaire was working, and its interest for reducing and simplifying data entry. They found it easy to use and potentially useful for gaining time. Clinicians said that “it was pretty easy to use”, “visually simple” and that “really we had just the data we needed in fact in the adaptive questionnaire, really everything that was a bit polluting for us at the level of the screen did not appear”. Clinicians appreciated having automatic data extraction from the EHR when possible, but also the possibility to manually review and complement the data in the adaptive questionnaire, or enter it from scratch when data extraction is not possible (*e.g.* if the GP uses an EHR that is not compatible, or does not agree on data transfers). More generally, all clinicians agreed that the CDSS will be useful to them and that the interfaces were appropriate.

## 5. Discussion

In this paper, we designed an adaptive questionnaire for facilitating patient condition entry in clinical decision support systems, with an application to polypharmacy and STOPP/START v2. We showed that this approach is able to reduce by almost two thirds the number of clinical conditions asked to the clinician, while having a very fast execution time.

In the presented work, we distinguished clinical conditions, typically disorders that the clinician has to enter, and non-clinical conditions, such as drug prescriptions and lab test results, that are usually available as structured data in EHR. However, if prescriptions or lab test results would not be available, the method can easily be adapted by treating them as we treated clinical conditions.

We compared two methods for ordering the clinical conditions: a simple heuristic and a metaheuristic (AFB). Both yielded the same results in terms of the number of conditions displayed, despite the metaheuristic is more sophisticated and allowed a patient-specific order. This can probably be explained by the fact that the ordering problem is theoretically NP-hard, but in practice, many clinical conditions are unrelated and independent from each other, at least in the STOPP/START v2 guideline. However, this might not be the case with other guidelines, thus having a more sophisticated option for solving the ordering problem remains interesting.

<b>Nervous system</b> <input type="checkbox"/> Alzheimer disease <input type="checkbox"/> Lewy body dementia <input type="checkbox"/> Parkinson disease <input type="checkbox"/> restless leg syndrome	<b>Psychology and psychiatry</b> <input type="checkbox"/> anxiety <input type="checkbox"/> depression	<b>sensory</b> <input type="checkbox"/> primary open-angle glaucoma	<b>Digestive</b> <input type="checkbox"/> GERD or peptic stenosis <input type="checkbox"/> constipation
<b>Endocrine, metabolism and nutrition</b> <input type="checkbox"/> diabetes with renal manifestations	<b>Genital and reproduction</b> <input type="checkbox"/> atrophic vaginitis	<b>Urinary</b> <input type="checkbox"/> dysuria or prostatism	<b>Cardiovascular</b> <input type="checkbox"/> atrial fibrillation <input type="checkbox"/> cardiac failure <input type="checkbox"/> coronary, cerebral, or peripheral vascular disease
<b>Respiratory</b> <input type="checkbox"/> asthma or COPD <input type="checkbox"/> chronic hypoxia	<b>Musculoskeletal</b> <input type="checkbox"/> fragility fracture <input type="checkbox"/> gout <input type="checkbox"/> osteopenia <input type="checkbox"/> osteoporosis <input type="checkbox"/> rheumatoid arthritis	<b>Others</b> <input type="checkbox"/> fall	

Figure 1: The adaptive questionnaire for a patient having an empty drug order.

<b>Endocrine, metabolism and nutrition</b> <input checked="" type="checkbox"/> diabetes with renal manifestations : <input type="checkbox"/> Non-insulin-dependent diabetes m <input type="checkbox"/> Insulin-dependent diabetes mellitus <input type="checkbox"/> Non-insulin-dependent diabetes mellitus <input type="checkbox"/> Malnutrition-related diabetes mellitus <input type="checkbox"/> Other specified diabetes mellitus <input type="checkbox"/> Unspecified diabetes mellitus <input type="checkbox"/> Glomerular disorders in diabetes mellitus E10-E14 with common fourth character .2	<b>Genital and reproduction</b> <input type="checkbox"/> atrophic vaginitis	<b>Urinary</b> <input type="checkbox"/> dysuria or prostatism <input checked="" type="checkbox"/> proteinuria ★	<b>Cardiovascular</b> <input type="checkbox"/> atrial fibrillation <input type="checkbox"/> cardiac failure <input type="checkbox"/> coronary, cerebral, or peripheral vascular disease
<b>Res</b>		<b>Others</b> <input type="checkbox"/> fall	

Figure 2: Excerpt of the adaptive questionnaire of Figure 1, after the user checked the condition “diabetes with renal manifestation”. Notice the drop-down combo box for choosing the appropriate ICD10 term, and the new condition “proteinuria” that appeared on the right.

Case	# drugs	Execution time	Conditions displayed			Rules triggered		
			STOPP (55)	START (30)	Total <sup>1</sup> (73)	STOPP (77)	START (34)	Total (111)
#1	11	0.075 s	11	21	28	5	3	8
#2	12	0.065 s	6	22	27	0	6	6
#3	15	0.061 s	5	17	20	4	4	8
#4	9	0.058 s	7	18	24	3	5	8
#5	6	0.057 s	4	20	24	2	3	5
#6	11	0.064 s	16	20	29	8	6	14
#7	13	0.072 s	6	20	25	3	4	7
#8	15	0.066 s	10	19	29	3	3	6
#9	10	0.061 s	13	22	34	4	2	6
#10	13	0.060 s	8	20	27	1	4	5
<b>Mean</b>	11.5	0.064 s	8.6	19.9	26.7	3.3	4.0	7.3
<b>(%)</b>			(15.6%)	(66.3%)	(36.6%)			

Table 1: Execution time for display rules, number of conditions displayed and number of rules triggered for 10 representative clinical cases of elderly patients with polypharmacy. <sup>1</sup>: the total of conditions displayed may be less than the sum of STOPP and START (e.g. case #1), because some conditions are common.



We opted for an unordered adaptive questionnaire, while most existing approaches are ordered (as seen in section 2). This choice was motivated by the fact that clinicians usually expect clinical conditions to be classified by anatomy (*e.g.* cardiac, renal...) and/or by etiology (*e.g.* infectious diseases), as they are in medical terminologies such as ICD10. On the contrary, in an ordered adaptive questionnaire, clinical conditions would have been ordered in the optimal order of entry, which is counterintuitive for clinicians.

We applied the proposed method to STOPP/START v2, a guideline for managing polypharmacy. This guideline is particularly favorable to the use of adaptive questionnaires, because all STOPP rules have at least one non-clinical condition (*i.e.* a drug prescription). If the method was applied to a guideline aimed at the treatment of a given disorder, such as type 2 diabetes or hypertension, the reduction of the number of conditions displayed is expected to be lower. However, we've seen in the results section that the adaptive questionnaire still reduce by about one third the number of conditions displayed for START rules. For other guidelines, the reduction is expected to be similar.

In the literature, the proposed CDSS for polypharmacy rely on the manual entry of clinical conditions from a medical terminology or a thesaurus (examples of such systems are PIM-Check [37], KALIS [38] and PRIMA-eDS [39]) or on the automatic extraction of clinical conditions from the EHR (*e.g.* in STRIPA [40], TRIM [41] and MedSafer [42]). For manual data entry, PIM-Check uses a flat list of about 150 terms. PRIMA-eDS also uses a flat list. In the PRIMA-eDS evaluation, the users explicitly reported that the manual data entry was “inconvenient and time-consuming”, preventing the use of the tool in daily practice [39]. The other studies relying on EHR data extraction, however, the connection to EHR is usually difficult to achieve, especially for community pharmacists: EHR are located at hospital or at the GP office, and not available to community pharmacists. In practice, EHR connection was achieved only in hospital or for GPs, or for pharmacists in very specific and centralized situations (namely, the Veterans Affairs in US, which operates centers integrating GPs and pharmacists, for TRIM [41]). But CDSS for polypharmacy are of particular use for community pharmacists when they perform medication reviews. As a consequence, it is very important to facilitate the manual data entry in polypharmacy CDSS, since the expected users usually do not have access to EHR.

The main limitation of this study is that, in most contexts other than polypharmacy, CDSS are used by physicians and not by pharmacists, and thus the users have access to the patient data in the EHR. However, the proposed adaptive questionnaire remains interesting as a tool for verifying at a glance the absence of error and missing data in the extracted patient data, before running the CDSS, or when the CDSS require very specific or trivial data that is unlikely to be present in the EHR. We encountered such a situation recently when designing a CDSS for the diagnosis and management of Covid-19 patients: the CDSS required many symptoms (*e.g.* cough, rhinorrhea,...) which are usually not entered in the EHR [43].

The perspective of this work includes the evaluation of the STOPP/START v2 implementation in clinical settings on real patients, and the application of the adaptive questionnaire to other clinical practice guidelines. The method may also be extended to more complex rule format, for instance rules of the form “if at least  $x$  conditions are present in a given list of  $y$  conditions, then...”. Finally, adaptive questionnaires might also be of interest for collecting patient-reported outcomes and more generally for data entry by the patient itself.

## 6. Conclusion

In conclusion, we proposed a method based on adaptive questionnaires for facilitating data entry in clinical decision support systems, and we applied the proposed methods to STOPP/START v2, a clinical practice guideline for the management of polypharmacy. The method considers a guideline implemented as a rule-based system, and proposes formula for translating the rules formalized from the guideline into rules determining which clinical conditions are mandatory to display to the clinician. Tests on STOPP/START v2 showed that this method can reduce by almost two thirds the size of the questionnaire.

## Supplementary files

Supplementary file #1: screenshot of the entire questionnaire, with the “adaptive” functionality disabled. It displays all clinical conditions for STOPP/START v2.

## Acknowledgments

This work was funded by the French Research Agency (ANR) through the ABiMed project [Grant No. ANR-20-CE19-0017].

## References

- [1] F. Hak, T. Guimarães, M. Santos, Towards effective clinical decision support systems: A systematic review, *PloS one* 17 (8) (2022) e0272846. doi:10.1371/journal.pone.0272846.
- [2] L. Souza-Pereira, N. Pombo, S. Ouhbi, V. Felizardo, N. Garcia, Clinical decision support systems for chronic diseases: A Systematic literature review, *Comput Methods Programs Biomed* 195 (2020) 105565. doi:10.1016/j.cmpb.2020.105565.
- [3] J. L. Kwan, L. Lo, J. Ferguson, H. Goldberg, J. P. Diaz-Martinez, G. Tomlinson, J. M. Grimshaw, K. G. Shojania, Computerised clinical decision support systems and absolute improvements in care: meta-analysis of controlled clinical trials, *BMJ (Clinical research ed.)* 370 (2020) m3216. doi:10.1136/bmj.m3216.
- [4] T. J. Bright, A. Wong, R. Dhurjati, E. Bristow, L. Bastian, R. R. Coeytaux, G. Samsa, V. Hasselblad, J. W. Williams, M. D. Musty, L. Wing, A. S. Kendrick, G. D. Sanders, D. Lobach, Effect of clinical decision-support systems: a systematic review, *Ann Intern Med* 157 (1) (2012) 29–43. doi:10.7326/0003-4819-157-1-201207030-00450.
- [5] S. Khairat, D. Marc, W. Crosby, A. Al Sanousi, Reasons For Physicians Not Adopting Clinical Decision Support Systems: Critical Analysis, *JMIR medical informatics* 6 (2) (2018) e24. doi:10.2196/medinform.8912.
- [6] A. Moxey, J. Robertson, D. Newby, I. Hains, M. Williamson, S. A. Pearson, Computerized clinical decision support for prescribing: provision does not guarantee uptake, *J Am Med Inform Assoc* 17 (1) (2010) 25–33. doi:10.1197/jamia.M3170.
- [7] E. G. Liberati, F. Ruggiero, L. Galuppo, M. Gorli, M. González-Lorenzo, M. Maraldi, P. Ruggieri, H. P. Friz, G. Scaratti, K. H. Kwag, R. Vespignani, L. Moja, What hinders the uptake of computerized decision support systems in hospitals? A qualitative study and framework for implementation, *Implementation Science* 12 (2017) 113.
- [8] Collier R, Electronic health records contributing to physician burnout, *Can Med Assoc J* 189 (45) (2017) E1405–E1406. doi:10.1503/cmaj.109-5522.
- [9] B. Séroussi, J. Bouaud, D. Sauquet, P. Giral, P. Cornet, H. Falcoff, J. Julien, Why GPs do not follow computerized guidelines: an attempt of explanation involving usability with ASTI guiding mode., *Stud Health Technol Inform* 160 (Pt 2) (2010) 1236–40.
- [10] B. H. de Mello, S. J. Rigo, C. A. da Costa, R. da Rosa Righi, B. Donida, M. R. Bez, L. C. Schunke, Semantic interoperability in health records standards: a systematic literature review, *Health and technology* 12 (2) (2022) 255–272. doi:10.1007/s12553-022-00639-w.
- [11] A. M. Sandoval, J. Díaz, L. Campillos Llanos, T. Redondo, Biomedical term extraction: NLP techniques in computational medicine, *International Journal of Interactive Multimedia and Artificial Intelligence* 5 (4) (2019) 51–59.
- [12] D. Alvarez-Estevez, I. Fernández-Varela, Addressing database variability in learning from medical data: An ensemble-based approach using convolutional neural networks and a case of study applied to automatic sleep scoring, *Comput Biol Med* 119 (2020) 103697. doi:10.1016/j.compbimed.2020.103697.

- [13] J. B. Lamy, V. Ebrahimiinia, C. Riou, B. Séroussi, J. Bouaud, C. Simon, S. Dubois, A. Butti, G. Simon, M. Favre, H. Falcoff, A. Venot, How to translate therapeutic recommendations in clinical practice guidelines into rules for critiquing physician prescriptions? *Methods and application to five guidelines*, *BMC Medical Informatics and Decision Making* 10 (2010) 31.
- [14] S. Pereira, S. Hassler, S. Hamek, C. Boog, N. Leroy, M. C. Beuscart-Zéphir, M. Favre, A. Venot, C. Duclos, J. B. Lamy, Improving access to clinical practice guidelines with an interactive graphical interface using an iconic language, *BMC medical informatics and decision making* 14 (1) (2014) 77.
- [15] A. Mouazer, R. Leguillon, B. Leroy, K. Sedki, C. Simon, H. Falcoff, M. Schuers, S. Dubois, C. Bousquet, L. Soualmia, C. Letord, S. Darmoni, J. Bouaud, B. Séroussi, R. Tsopra, J. B. Lamy, ABiMed: Towards an innovative clinical decision support system for medication reviews and polypharmacy management, in: *Studies in health technology and informatics (ICIMTH)*, Vol. 289, 2021, pp. 61–64.
- [16] A. Mouazer, R. Tsopra, K. Sedki, C. Letord, J. B. Lamy, Decision-support systems for managing polypharmacy in the elderly: A scoping review, *J Biomed Inform* 130 (2022) 104074.
- [17] M. Michiels-Corsten, N. Gerlach, T. Schleeff, U. Junius-Walker, N. Donner-Banzhoff, A. Viniol, Generic instruments for drug discontinuation in primary care: A systematic review, *Br J Clin Pharmacol* 86 (7) (2020) 1251–1266. doi:10.1111/bcp.14287.
- [18] I. A. Scott, P. I. Pillans, M. Barras, C. Morris, Using EMR-enabled computerized decision support systems to reduce prescribing of potentially inappropriate medications: a narrative review, *Therapeutic advances in drug safety* 9 (9) (2018) 559–573. doi:10.1177/2042098618784809.
- [19] D. O'Mahony, D. O'Sullivan, S. Byrne, M. N. O'Connor, C. Ryan, P. Gallagher, STOPP/START criteria for potentially inappropriate prescribing in older people: version 2, *Age Ageing* 44 (2) (2015) 213–8. doi:10.1093/ageing/afu145.
- [20] J. B. Beuscart, S. Pelayo, L. Robert, S. Thevelin, S. Marien, O. Dalleur, Medication review and reconciliation in older adults, *European geriatric medicine* 12 (3) (2021) 499–507. doi:10.1007/s41999-021-00449-9.
- [21] A. Girgensohn, B. Zimmermann, A. Lee, B. Burns, M. E. Atwood, *Human-Computer Interaction*, 1995, Ch. Dynamic forms: An enhanced interaction abstraction based on forms, pp. 362–367.
- [22] F. Sadki, J. Bouaud, G. Guézennec, B. Séroussi, Semantically Structured Web Form and Data Storage: A Generic Ontology-Driven Approach Applied to Breast Cancer, *Stud Health Technol Inform* 255 (2018) 205–209.
- [23] E. Mwamikazi, P. Fournier-Viger, C. Moghrabi, R. Baudouin, A dynamic questionnaire to further reduce questions in learning style assessment, in: *IFIP International conference on artificial intelligence applications and innovations*, Berlin, Heidelberg, 2014, pp. 224–235.
- [24] A. Ortigosa, P. Paredes, P. Rodríguez, AH-questionnaire: An adaptive hierarchical questionnaire for learning styles, *Computers & Education* 54 (2010) 999–1005.
- [25] K. Chen, H. Chen, N. Conway, J. M. Hellerstein, T. S. Parikh, USHER: Improving data quality with dynamic forms, in: *IEEE 26th International Conference on Data Engineering (ICDE)*, 2010, pp. 321–332.
- [26] C. Bonesana, F. Mangili, A. Antonucci, ADAPQUEST: A Software for Web-Based Adaptive Questionnaires based on Bayesian Networks, in: *AI4EDU: Artificial Intelligence For Education*, workshop at IJCAI, Virtual Event, 2021.
- [27] C. Liu, C. Yuan, A. M. Butler, R. D. Carvajal, Z. R. Li, C. N. Ta, C. Weng, DQuest: dynamic questionnaire for search of clinical trials, *J Am Med Inform Assoc* 26 (11) (2019) 1333–1343. doi:10.1093/jamia/ocz121.
- [28] R. C. Gibson, M. M. Bouamrane, M. D. Dunlop, Ontology-driven, adaptive, medical questionnaires for patients with mild learning disabilities, in: *International conference on innovative techniques and applications of artificial intelligence*, 2019, pp. 107–121.
- [29] X. Kortum, L. Grigull, W. Lechner, F. Klawonn, A dynamic adaptive questionnaire for improved disease diagnostics, in: *International symposium on intelligent data analysis*, 2017, pp. 162–172.
- [30] P. C. Sherimon, P. V. Vinu, K. Reshmy, T. Youssef, A. Yousuf, A. Yousuf, Adaptive questionnaire ontology in gathering patient medical history in diabetes domain, in: *International conference on advanced data and information engineering (DAENG)*, 2014, pp. 453–460.
- [31] A. M. Villalba-Moreno, M. Galván-Banqueri, A. Rodríguez-Pérez, M. D. Toscano-Guzmán, C. López-Hermoso, S. Sánchez-Fidalgo, B. Santos-Ramos, E. R. Alfaro-Lara, Chronic-pharma: New Platform for Chronic Patients Pharmacotherapy Optimization, *J Med Syst* 46 (4) (2022) 18. doi:10.1007/s10916-022-01808-0.
- [32] Lamy JB, *Advances in nature-inspired computing and applications*, Springer, 2019, Ch. Artificial Feeding Birds (AFB): a new metaheuristic inspired by the behavior of pigeons, pp. 43–60.
- [33] Lamy JB, A data science approach to drug safety: Semantic and visual mining of adverse drug events from clinical trials of pain treatments, *Artif Intell Med* 115 (2021) 102074. doi:https://doi.org/10.1016/j.artmed.2021.102074.
- [34] Lamy JB, Owlready: Ontology-oriented programming in Python with automatic classification and high level constructs for biomedical ontologies, *Artif Intell Med* 80 (2017) 11–28.
- [35] C. J. A. Huibers, B. T. G. M. Sallevelt, D. A. de Groot, M. J. Boer, J. P. C. M. van Campen, C. J. Davids, J. G. Hugtenburg, A. M. A. Vermeulen Windsant-Van den Tweel, H. P. J. van Hout, R. J. van Marum, M. C. Meulendijk, Conversion of STOPP/START version 2 into coded algorithms for software implementation: A multidisciplinary consensus procedure, *Int J Med Inf* 125 (2019) 110–117. doi:10.1016/j.ijmedinf.2018.12.010.
- [36] A. Mouazer, K. Sedki, R. Tsopra, J. B. Lamy, Speak-PIM, towards a framework for the automatic detection of potentially inappropriate prescriptions, in: *Studies in health technology and informatics (MIE)*, Vol. 294, Nice, France, 2022, pp. 460–464.
- [37] A. Desnoyer, A. L. Blanc, V. Pourcher, M. Besson, C. Fonzo-Christe, J. Desmeules, A. Perrier, P. Bonnabry, C. Samer, B. Guignard, PIM-Check: development of an international prescription-screening checklist designed by a Delphi method for internal medicine patients, *BMJ open* 7 (7) (2017) e016070. doi:10.1136/bmjopen-2017-016070.
- [38] A. Shoshi, U. Müller, A. Shoshi, V. Ogultarhan, R. Hofestädt, KALIS - An eHealth System for Biomedical Risk Analysis of Drugs, *Stud Health Technol Inform* 236 (2017) 128–135.
- [39] A. Rieckert, C. Sommerauer, A. Krumeich, A. Sönnichsen, Reduction of inappropriate medication in older populations by electronic decision support (the PRIMA-eDS study): a qualitative study of practical implementation in primary care, *BMC family practice* 19 (1) (2018) 110. doi:10.1186/s12875-018-0789-3.
- [40] M. C. Meulendijk, M. R. Spruit, P. A. Jansen, M. E. Numans, S. Brinkkemper, STRIPA: A rule-based decision support system for medication reviews in primary care, in: *European Conference on Information Systems (ECIS)*, Münster, Germany, 2015.
- [41] K. M. Niehoff, N. Rajeevan, P. A. Charpentier, P. L. Miller, M. K. Goldstein, T. R. Fried, Development of the Tool to Reduce Inappropriate Medications (TRIM): A Clinical Decision Support System to Improve Medication Prescribing for Older Adults, *Pharmacotherapy* 36 (6) (2016) 694–701. doi:10.1002/phar.1751.
- [42] E. G. McDonald, P. E. Wu, B. Rashidi, A. J. Forster, A. Huang, L. Pilote, L. Papillon-Ferland, A. Bonnici, R. Tamblin, R. Whitty, S. Porter, K. Battu, J. Downar, T. C. Lee, The MedSafer Study: A Controlled Trial of an Electronic Decision Support Tool for Deprescribing in Acute Care, *J Am Geriatr Soc* 67 (9) (2019) 1843–1850. doi:10.1111/jgs.16040.
- [43] J. B. Lamy, M. Jammal, M. Saikali, C. Mourad, C. Abi Khalil, A. Saab, Fish-eye visualization and multi-path trees for presenting clinical practice guidelines: Methods and application to Covid-19, in: *International Conference Information Visualisation (iV)*, 2023.