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# Methods Used to Compare Narrative Clinical Practice Guidelines: A Scoping Review

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**Abstract.** Guideline-based clinical decision support systems (CDSSs) need the most recent evidence for reliable performance, making the provision of regularly updated clinical practice guidelines (CPGs) a major issue. Some international guidelines are renewed in short intervals and can be used for checking the status of given national guidelines with regard to the most recent evidence. Considering the volume of medical data and the number of CPGs published, computerized comparison of clinical guidelines can be an effective method. We performed a scoping review to evaluate the methods used for comparing two CPGs. We searched for methods for extracting CPG components and for methods used for comparing CPGs at different levels of abstraction. In each case, computerized and semi-computerized methods were recognized. Expert knowledge has yet a determinant role for assessing the comparisons, this role being more prominent for the extraction of semantic rules and the resolution of inconsistencies.

**Keywords.** Clinical practice guidelines, ontology, natural language processing, machine learning.

## 1. Introduction

Clinical practice guidelines (CPGs) are used to implement the knowledge bases of guideline-based clinical decision support systems (CDSSs) [1]. Because medical knowledge is continuously evolving, CPGs must be revised regularly.

Ebmfrance.net is a platform of CPGs for general practitioners (GPs), developed in France by the Collège de la Médecine Générale (CMG). It includes approximately 1000 CPGs written in the French language, scientifically validated and regularly updated. Most of them come from the Finnish collection "EBM Guidelines" translated into French and adapted by the CMG editorial team. Because it is highly labor consuming to maintain all these national CPGs updated, the project is to use

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internationally available CPGs which are renewed regularly as a reference to establish the status of national CPGs with regard to the latest evidence and to engage the CMG editorial team only on those CPGs that need to be revised. The aim of this paper is to present a scoping review of the literature we conducted to analyze the methods used for comparing narrative CPGs.

## 2. Methods

On February 2022, we performed a literature search over the last 10 years (2012–2022) using PubMed and Google Scholar. Three separated queries of (([computerized comparison] OR [manual comparison]) AND [clinical guidelines]), (computerized comparison of clinical guidelines), (computerized evaluation of clinical guidelines) were used for PubMed. Three separated queries of reformulated similar terms were used for Google Scholar search. We filtered the returned articles on the basis of title, abstract. We analyzed the methods used for textual and semantic comparison of texts and guidelines. We also inspected the references section of resulting articles for including more relevant articles.

We analyzed the different computerized methods used, including text mining techniques, NLP, semantic analysis, supervised or unsupervised machine learning algorithms. Methods were finally compared according to the phase they were used in the analysis of CPGs: extraction of concepts, extraction of rules and semantics, and comparison between guidelines at different levels of data abstraction.

## 3. Results

Searching PubMed and Google Scholar with mentioned queries resulted in 397 and 223 articles respectively. After merging the two lists of returns and removing duplicates, when keeping only the most relevant papers, 11 articles remained for the analysis (Figure 1). This process was done by MA and repeated by AR with an inter-rater reliability score of 66%. We considered three phases for comparing CPGs.

### *3.1. Extraction of concepts*

Extraction of concepts is performed by using rule-based methods for searching an exact match of words [2] or using a neural network with attention mechanism when the text does not contain standard medical terminologies [3,4]. Extracted concepts are then “normalized” according to suitable terminological dictionaries of the domain [2,3]. This process was done by using automatic methods [2] or using expert knowledge [5].

### *3.2. Extraction of rules and semantics*

In this phase, recommendation statements and “if – then” rules are extracted in order to build a computer-interpretable version of narrative CPGs. Extraction of recommendation statements is performed by using several machine learning algorithms with high accuracy score values [6]. Although some studies proposed to use Natural Language Understanding (NLU) approaches for extracting semantics and rules from

CPGs [7], the process of automatic extraction of "if – then" phrases from a narrative text is not yet satisfactory. This phase is still handled by a human domain expert [1,8].

### *3.3. Comparison between guidelines at different levels of data abstraction*

Comparing CPGs is performed at different levels. At the concept level, different methods based on the similarity between medical concepts were evaluated against human expert measurements [9]. Mathematical methods are generally based on two methods, (i) "ontological step-based" methods which use the minimal number of steps joining two concepts in an ontology, or (ii) "embedding matrices" used for calculation of similarity (for example the cosine similarity) [9,10].

Some other studies report results based on the assessment of CPG conceptual coverage intersection [5,11]. This method has been used for comparing three CPGs for the management of arterial hypertension [5] and for comparing five CPGs of Potentially Inappropriate Medications (PIM) from different sources. Authors used visualization methods for showing the intersections between CPGs [11].

Another study used ontologies for mapping patient profiles and rules from two CPGs and compared the inferred therapeutic recommendations [1]. Inferred actions in these scenarios can be conflicting and may need to be solved by a human expert [1,8].

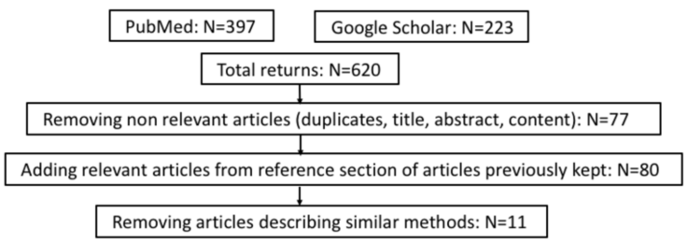


**Figure 1.** Flowchart of the selection of study articles

## 4. Discussion

Updating CPGs is essential for appropriate functioning and reliability of guideline-based CDSSs. This can be achieved by comparing local CPGs to some international and regularly updated CPGs. From a practical point of view, several steps should be considered, the first of them being concepts extraction and organization to building a computer-interpretable representation of CPGs. Machine learning algorithms and rule-based NLP methods are used for the extraction of medical concepts from texts [2,3]. There are modern transformer and attention mechanism neural networks for extraction of concepts [3,4]. However, when the exact medical concept term exists in a text (in narrative CPGs) searching for a concept can be done effectively using less complex rule-based text extraction methods [4].

Automatic searching for rules and recommendations in CPGs is a major issue yet to be solved. Machine learning algorithms are used to extract recommendation statements from the background knowledge of CPGs [6]. There are some promising experiments using NLU approaches [7], however, effective extraction of (if – then) rules and resolution of inconsistencies are done by a domain expert [1], demonstrating that effective algorithms are to be developed.

Comparing CPGs with knowledge-based approaches can be done at several levels. Both ontologies and embedding matrices are used for similarity measurements [9,10]. Each embedding matrix is to be verified according to its knowledge source of training, dimensions, and conceptual coverage [10] to make reliable measurements. Another level of comparison between CPGs is comparing conceptual coverage. This task may be done using visualization methods [5,11] to provide intuitive comparisons [11].

CPGs can also be compared according to the inferred actions resulting from different (or similar) patient profiles represented in a domain ontology. In a study, for a patient with multi-morbidity, (if-then) rules extracted from three CPGs were applied to an ontology and the inferred actions from the same patient profile were evaluated. Authors proposed that when a top-down approach makes a conflict, a bottom-up approach should be performed for resolving the conflict by choosing only a single (the most specific patient profile) path [8].

In conclusion, there is no satisfactory automatic approach for comparing two CPGs. Extraction of concepts can be done effectively by NLP methods using standard medical terminologies and extraction of rules and recommendations largely relies on a human domain expert. Automatic ontological reasoning can be used effectively for analyzing the inferred actions for different patient profiles. In some cases, assessing CPG conceptual coverage provides sufficient information for comparing their contents.

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