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This is the author's manuscript

Original Citation:

Availability:
This version is available http://hdl.handle.net/2318/1640616 since 2017-10-27T14:53:55Z

Publisher:
ACM

Published version:
DOI:10.1145/3019612.3019713

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(Article begins on next page)
This is the author's final version of the contribution published as:


The publisher's version is available at: http://dl.acm.org/ft_gateway.cfm?id=3019713&ftid=1875902&dwn=1

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Temporal reasoning techniques for the analysis of interactions in the treatment of comorbid patients

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ABSTRACT
Clinical practice guidelines are assuming a major role in the medical area, to provide physicians with evidence-based recommendations for the treatment of single pathologies. The treatment of comorbid patients (i.e., patients affected by multiple diseases) is one of the main challenges for the modern healthcare. It requires the development of new methodologies, supporting physicians in the treatment of interactions between guidelines. Several Artificial Intelligence approaches have started to face such a challenging problem. However, current approaches have a substantial limitation: they do not take into account the temporal dimension. This is a strong limitation. For instance, the effects of two actions taken from different guidelines may potentially conflict, but practical conflicts happen only if effects of such actions overlap in time. In this paper, we propose an approach to support the temporal detection of interactions. Artificial intelligence temporal reasoning techniques, based on temporal constraint propagation, are widely exploited to such a purpose.

CCS Concepts
• CCS → Information systems → Information systems applications → Decision support systems → Expert systems
• CCS → Applied computing → Life and medical sciences → Health care information systems
• CCS → Computing methodologies → Artificial intelligence → Knowledge representation and reasoning → Temporal reasoning

Keywords
Computer-interpretable clinical guidelines; comorbidity treatment; guideline interaction detection; temporal reasoning; medical knowledge representation.

1. INTRODUCTION
Clinical Practice Guidelines (CPGs) are “systematically developed statements to assist practitioner and patient decisions about appropriate health care in specific clinical circumstances” [1]. Thousands of CPGs have been devised in the last years. For instance, the Guideline International Network includes more than 100 organizations representing 48 countries and provides a library of more than 6500 CPGs. The adoption of computerized approaches to acquire, represent, execute and reason with CPGs can further increase the advantages of CPGs. Thus, in the last twenty years, several different approaches to Computer-Interpretable Guidelines (henceforth CIGs) have been developed (see, e.g., [2], [3]).

By definition, clinical guidelines address specific clinical circumstances (i.e., specific diseases). Unfortunately, in many cases patients are affected by more than one disease. The treatment of comorbid patients (i.e., patients affected by multiple diseases) is one of the main challenges for the modern health care, also due to the aging of population and the consequent increase of chronic diseases.

Though some CPGs covering frequently occurring comorbidities might be devised, the approach of considering all the possible combinations of pathologies does not scale up. Thus, there is a need for formal methodologies to support physicians in the detection and resolution of interactions between guidelines, and, ultimately, in the process of merging two or more guidelines. This is an increasingly “hot topic” within the Medical Informatics community, and several approaches have been proposed in the last years (see Section 5). In such approaches, new methodologies, mostly based on Artificial Intelligence techniques, have been proposed. Despite the treatment of time in CIGs has received some attention (see, e.g., [4], [5]), to the best of our knowledge, until now no CIG approach in the literature has taken into consideration the temporal dimension in the study of interactions. This is a crucial limitation. Indeed, a non-temporal analysis can only detect theoretically possible interactions between actions in different CIGs, identifying, e.g., a potential conflict between their effects. However, as long as no temporal analysis is performed, such an interaction is only “potential”: actual interactions occur in time, i.e., just in case that the considered effects overlap in time. The approach in this paper is, to the best of our knowledge, the first one starting to face such a challenging problem. To do so, an extended representation formalism has to be identified, to model time and temporal interactions, as well as advanced temporal reasoning techniques, to discover whether the effects of potentially conflicting actions overlap in time. In this paper, we propose an advanced Artificial Intelligence approach facing such issues, developed on top of the GLARE system [6], [7]. Notice, however, that the methodology we propose is largely system-independent.

The paper is organized as follows. Section 2 briefly introduces GLARE and previous work to cope with comorbidities in GLARE. Section 3 describes the extensions to the representation needed to deal with time. Section 4 discusses our solution to the detection of temporal interactions. Finally, Section 5 proposes related works and comparisons.

2. PRELIMINARIES: GLARE
GLARE (Guideline Acquisition, Representation and Execution) [6], [7] has been built starting from 1997 in a long-term
cooperation between the Department of Computer Science of the University of Piemonte Orientale, Alessandria, Italy and the Azienda Ospedaliera San Giovanni Battista in Turin (one of the largest hospitals in Italy). GLARE supports the use of advanced artificial intelligence techniques and decision-support techniques in the treatment of CIGs [7] (a comparison of GLARE with other approaches coping with CIGs can be found in [3]). In GLARE, a CIG can be represented as a hierarchical graph, where nodes are the actions to be executed and arcs are the control relations linking them. GLARE distinguishes between atomic and composite actions (plans), where atomic actions represent simple steps in a CIG and plans represent actions that can be defined in terms of their components via the has-part relation. GLARE adopts different types of atomic actions. In this paper, we just focus on work and pharmacological actions.

Actions in a CIG are connected through control relations, establishing which actions can be executed next and in what order. In particular, the sequence relation explicitly establishes what the following action to be executed is; the alternative relation describes which alternative paths stem from a decision action and the repetition relation states that an action has to be repeated several times. The constrained relation is used in order to express more complex temporal constraints between actions (see Section 3).

2.1 Coping with comorbidities in GLARE: previous work

Starting from 2013, GLARE has started to be extended to cope with comorbidities. The long-term goal of such a work is that of providing physicians with a domain-independent and guideline-independent set of tools and methodologies:

1. to detect and analyze the interactions between CIGs,
2. to solve the detected interactions,
3. to merge multiple CIGs in the treatment of a specific comorbid patient at hand.

In this paper, we focus on issue (1) only. In [8], we identified three different knowledge levels at which interactions might occur: (i) level of the goals of the CIG actions, (ii) level of the effects of the actions, and (iii) level of the drugs recommended by pharmacological actions. [8] also proposes a knowledge base (henceforth called ontological model) representing the interactions at the different levels and provided support for interactive physician-driven analysis of the interactions at the different levels (without considering time). Interactions can be (i) automatically detected by a reasoning tool or (ii) manually inserted in the knowledge base. However, querying the knowledge base and simply giving as output all the interactions between all the actions belonging to the two CIGs is not useful for physicians during the analysis. The output would contain too many elements, most of which would be irrelevant. For such a reason, in [9] we proposed a tool to support physicians to navigate CIGs at different levels of abstraction, allowing them to focus on relevant parts of the CIGs and to compare only those actions considered important and potentially interacting.

Example 1 (Description and non-temporal analysis). The running example is a situation in which a patient treated for deep venous thrombosis develops a respiratory tract infection. We also assume that the patient is currently treated with Warfarin (an anticoagulant drug) for the thrombosis. The CIG for the respiratory tract infection suggests, among the others, the treatment with Erythromycin (an antibiotic). The drug interaction between Erythromycin and Warfarin is well known in medical literature (see, e.g., [10]) and, in our model, it is represented by an interaction between the anticoagulant effect of Warfarin and the metabolism reduction caused by Erythromycin. Their concomitant use increases the anticoagulant effect of Warfarin, raising the risk of bleedings.

Using the non-temporal detection of interactions facilities of GLARE, the physician navigates the two CIGs. Then, s/he focuses on the Warfarin treatment (for the first CIG) and on the Erythromycin treatment (for the second CIG). At such a level of detail, the (simplified) CIG for thrombosis contains three Warfarin administrations (W1, W2 and W3), as well as a calculation of the International Normalized Ratio (INR) and its evaluation (INR evaluation). See the upper part of Figure 1. In the lower part of Figure 1 we show the actions of Erythromycin administration (E1 and E2) in the respiratory infection CIG.

In the example, we suppose that the first two Warfarin administrations have been already executed. On the other hand, the Erythromycin treatment contains two Erythromycin administrations, none of which has been executed yet. The physician may now want to know whether the last executed Warfarin administration (W2) can interact with the first Erythromycin administration that has to be executed next (E1). GLARE detects such interaction from the non-temporal point of view. However, a temporal analysis is required to ascertain whether the interaction can occur in time.

3. REPRESENTATION OF TEMPORAL INFORMATION

In this section we describe the temporal formalism we adopt for CIGs, the temporal phenomena involved by comorbidities and the extension of the temporal formalism to deal with such phenomena. Our temporal representation satisfies two main requirements:

i. it is expressive enough to represent the temporal phenomena we focus on and
ii. its temporal constraints can be translated into STP [11].

3.1 Representing Temporal Constraints

We admit two basic temporal entities: Time Intervals and Time Points. We consider both qualitative and quantitative temporal constraints between temporal entities. Qualitative constraints represent the relative position of two temporal entities. We use a fragment of Vilain’s algebra in [12] to represent qualitative

![Figure 1. Focused part of the venous thrombosis (upper part of the figure) and respiratory tract infection (lower part) CIGs, in the analysis of interactions.](image)
relations between time points and time intervals. Vilain distinguishes between point-point constraints (●Before, ●After, ●Equals), point-interval constraints (●Before, ●Begins, ●During, ●Ends, …) and interval-interval constraints (Before, After, Ends …) (the latter are usually known as Allen’s basic temporal relations [13]). Vilain considers also arbitrary disjunctions of such constraints. In our approach, we restrict our attention to the subset of Vilain’s constraints that can be expressed in STP, i.e., on the continuous pointizable constraints [14]. On the other hand, quantitative constraints consider metric time. In our approach, they are characterized by a minimum and a maximum value bounding the span of time between two time points and a time unit for the bounds. It is worth stressing that such a representation supports temporal indeterminacy, since the maximum and minimum values can be different. We identify three basic types of quantitative constraints: Date, Delay and Duration. Dates model “absolute” metric time. Indeed, a date can be represented by a constraint between a time point and a reference time, which is a fixed point on the timeline unique for all the dates. Durations characterize a time interval representing the distance between its ending and starting points. Delays represent the distance between two general time points.

3.2 Temporal Extension of the Knowledge Sources

To analyse CIG interactions, we have to consider different sources of temporal information: the two interacting CIGs, the log of the CIG actions already executed on the patient, and the knowledge base (ontological model) describing actions, and their interactions.

CIG temporal knowledge. GLARE allows to annotate the arcs between actions (in particular, the sequenced and the constrained arcs) with temporal constraints expressed using the formalism in Section 3.1.

For example, the temporal constraints concerning the part of the venous thrombosis CIG in Figure 1 are shown in the upper part of Figure 2. Warfarin is usually administered once a day. Thus, the CIG for thrombosis contains temporal constraints between consecutive warfarin administrations (W1, W2 and W3) binding the delay between them to be greater than or equal to one day and to be less than two days (constraints between non-consecutive administrations can be inferred later by our STP reasoner). In the example, we work at the granularity of days. Notice that both quantitative and qualitative constraints are represented.

Log knowledge. In many medical contexts, it is not realistic to assume to know the exact execution time of each action executed on the patient. We thus support imprecise temporal information in the log, represented through the formalism proposed in Section 3.1. For example, the log temporal constraints for the Warfarin administrations may be:

- Warfarin treatment started on 01/04/2015
- W1 executed on 01/04/2015
- W2 executed ●after● W1

Temporal information in the Knowledge base (ontological model). The ontological knowledge contains temporal information about the interacting elements. In particular, the ontological knowledge models the delay between action execution and the manifestation of their effects, and the durations of such effects (expressed through the formalism in Section 3.1).

4. TEMPORAL REASONING

To detect temporal interactions between actions, temporal reasoning on the above pieces of temporal information must be provided.

We defined two main modules to manage the temporal extension of our system (see Figure 3). The first one, the “Visualization” module, provides a high-level interface to communicate with users, hiding the details of the underlying second module, i.e., the “Temporal Reasoner” module. The Temporal Reasoner module is subdivided into five sub-modules. “Extraction” and “Translation” modules collect the temporal constraints from the log, the CIGs and the ontological model and translate them into STP. The remaining three modules are organized in a “multi-layered structure”. The innermost module is the standard STP constraint propagation framework developed by Dechter et al. [11]. In STP, temporal constraints are represented as bounds on differences of the form c≤P1-P2≤d, where P1 and P2 are time points, and c and d represent the minimum and maximum distance between them. Correct and complete temporal reasoning in STP can be performed through an application of Floyd-Warshall’s all-pairs shortest-paths algorithm, which operates in cubic time, and provides as output a minimal network, i.e., the strictest possible
distances between each pair of time points, or an inconsistency [11]. However, such a standard approach must be extended to cope with the phenomena related to interaction detection. We do so in the “Extended reasoning” module, which extends STP to provide more complex reasoning tasks. Then, the outer layer (“Result Interpretation”) module interprets results of temporal reasoning. It is worth noting that the overhead of our extensions is negligible since their complexity is dominated by the complexity of STP constraint propagation.

**Example 1 (Query).** We assume that the physician is interested in the interaction between the Warfarin and the Erythromycin treatments. Specifically, s/he may want to know whether the last executed Warfarin administration W2 can interact with the first (not performed yet) administration of Erythromycin E1.

### 4.1 Constraint extraction and translation

The temporal constraints from the CIGs, the log and the knowledge base are collected, and then translated into STP (the translation is easy – operating in linear time and space – and it is omitted for the sake of brevity). To collect the temporal constraints, we have devised an algorithm that, starting from the temporal entities involved in an interaction, navigates backward and across the knowledge sources, retrieving all (and only) the temporal constraints that can influence them.

First, we extract from the knowledge base the temporal constraints between the actions (involved in the interactions) and their effects. Then, we extract from the log the temporal constraints concerning the CIG actions that have been already executed on the patient.

Finally, from the CIGs we extract the temporal constraints imposed by control arcs between the interacting actions and the other actions belonging to the same CIG, and corresponding to the executed actions in the log. Once extracted the relevant temporal information, we translate it into STP. It is worth noticing that all the constraints expressed through our formalism (see Section 3.1) can be automatically mapped to STP.

**Notation.** Henceforth, given an action Act, if Act is punctual, Act_p represents the time point in which Act is executed. If Act is durative, Act_s represents its starting point and Act_t its ending point.

**Example 1 (Extraction and Translation).** Considering a granularity of days and reference time RT = 01/04/2015 (corresponding to the time of execution of the first Warfarin administration), the STP constraints derived from the Warfarin administrations (CIG for venous thrombosis) of Example 1 are:

(C1) \(1 \leq AN_{E2} - W2_{P} \leq 1\)

(C2) \(1 \leq AN_{B2} - AN_{E2} \leq 4\)

(C3) \(0 \leq W1_{P} - RT \leq 0\)

(C4) \(0 < W2_{P} - W1_{P} \leq +\infty\)

(C5) \(1 \leq W2_{P} - W1_{P} < 2\)

Constraints C1 and C2 are extracted from the ontological knowledge while constraints C3, C4 and C5 are extracted from CIG and log. Similarly, constraints regarding the CIG for respiratory tract infection are collected and translated, obtaining the following:

(C6) \(0 \leq RM_{E} - E1_{P} \leq 1\)

1 Legend for the time points: \(W_{NP}\) time of execution of the \(n^{th}\) warfarin administration; \(AN_{N}\) and \(AN_{E}\) endpoints of the anticoagulant effect of the \(n^{th}\) warfarin administration; RT reference time; \(E_{NP}\) time of execution of the \(n^{th}\) erythromycin administration; \(RM_{N}\) and \(RM_{E}\) endpoints of the reducing metabolism effect of the \(n^{th}\) erythromycin administration.

### 4.2 Extended STP Reasoning

Unfortunately, the “standard” STP approach is not sufficient to cope with our temporal interaction problem. Thus, we provide a module of our temporal reasoner which extends STP to cope with partonomic temporal reasoning and with class-instance reasoning.

#### Partonomic temporal reasoning

Partonomic relations in the CIGs (i.e., the fact that composite actions can be defined in terms of their components) induce temporal constraints that have to be represented in the STPs. Indeed, this phenomenon can be easily managed on top of STP. In particular, when an action B is part of an action A, we have the STP constraints \(0 < B_{R} - A_{2} \leq +\infty\) and \(-\infty \leq B_{R} - A_{2} \leq 0\). For instance, in Example 1, the action E1 is part of the high-level action Erythromycin treatment. Then, our system extracts also the partonomic constraints \(0 \leq E1_{P} - T_{E} \leq +\infty\) and \(-\infty \leq E1_{P} - T_{E} \leq 0\) (where \(T_{E}\) and \(T_{E}\) are the starting and ending points representing the action Erythromycin treatment and E1 is the time point representing the punctual action E1).

#### Class-instance reasoning

The temporal constraints in the CIGs can be considered constraints on classes of actions, which are instantiated each time a CIG is executed on a specific patient. Thus, the problem of checking whether a specific execution (instance) of a CIG satisfies the temporal constraints of a CIG corresponds to checking whether the temporal constraints of the instances satisfy the temporal constraints of the classes. This problem has been dealt with in [4]. In that work, the authors have considered the problem of “inheriting” the temporal constraints from classes of events to instances of events. They have also singled out two issues that, in general, make the inheritance a difficult problem: correlation and observability. Given a temporal constraint between two classes of actions, correlation concerns the issue of identifying the corresponding pair of instances of such actions that have to inherit the temporal constraint. Observability concerns the issue of knowing whether and/or to what extent one can assume that the executed actions are indeed observed (and recorded). As stated in [4], in the CIG domain, which is also the context we consider in this paper, it is possible to assume that correlation is exactly known and that there is full observability of the instances. Therefore, it is possible to cope with the class-instance temporal reasoning by merging in a single STP both the constraints between classes and the constraints between instances, and then performing STP temporal reasoning. For each pair of time points, STP can take into account just one minimum and one maximum distance; in case both the CIG and the LOG provide such pieces of information, they have to be “merged” by considering the maximum of the minimum distances, and the minimum of the maximum distances. For instance, given two time points A and B, and two constraints \(c_{1} \leq B - A \leq d_{1}\) and \(c_{2} \leq B - A \leq d_{2}\), the “merge” (to be inserted in the STP) is \(max(c_{1}, c_{2}) \leq B - A \leq min(d_{1}, d_{2})\). In our example, constraints C4 and C5 are both referred to the difference \(W2_{P} - W1_{P}\). Then, the resulting constraint is \(1 \leq W2_{P} - W1_{P} < 2\).

### 4.3 Result Interpretation

We need to check whether the times of the effects of two possibly interacting actions in two CIGs intersect in time. Considering two effects A and B, the answer YES must be provided just in case A and B necessarily intersect in time. Such a test can be directly performed through an inspection in the **minimal network** produced...
by the application of an all-pairs shortest paths algorithm to the temporal constraints. Specifically, to ascertain the intersection we have to check whether the following condition is necessarily true:

\[ (A_g - B_g \leq 0 \land B_g - A_g \leq 0) \lor (B_S - A_S \leq 0 \land A_S - B_S \leq 0) \]  
(Condition 1)

where \( A_g \) (\( B_g \)) and \( A_S \) (\( B_S \)) indicate respectively the starting and ending points of \( A \) (\( B \)). On the other hand, the non-intersection is ascertained by checking the necessity of the following condition:

\[ (A_g - B_S < 0) \lor (B_S - A_g < 0) \]  
(Condition 2)

Notice that, since Condition (1) is the negation of Condition (2), we can easily verify the necessity of one of the two conditions by verifying the non-possibility of the other one and vice versa.

**Example 1 (Solution Existence Verification).** The minimal network resulting our example is shown in Table 1.

To ensure the intersection, the intervals \([AN2_S, AN2_g]\) and \([RM1_S, RM1_g]\) must overlap, thus the Condition (1) must hold, i.e.:

\[ (AN2_S - RM1_S \leq 0 \land RM1_S - AN2_S \leq 0) \lor (RM1_S - AN2_S \leq 0 \land AN2_S - RM1_S \leq 0) \]

To ensure the non-intersection, the Condition (2) must hold, i.e.:

\[ (AN2_S - RM1_S < 0) \lor (RM1_S - AN2_S < 0) \]

Given the minimal network, both the conditions are possible, but not necessary. Then, the answer of the system is MAYBE.

**Table 1. Minimal network of the temporal constraints (after temporal reasoning)**

<table>
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<tr>
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<th>W3</th>
<th>W4</th>
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<th>AN2</th>
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5. RELATED WORK AND CONCLUSIONS

The treatment of comorbid patients is one of the main challenges for the modern healthcare, and several approaches are recently emerging to cope with the integration of CIGs to manage comorbid patients. Among them, the approach in [15] is the most similar to ours. It provides a conceptual model for medical actions and detects interactions using such a model and rules. However, it does not consider time. Other approaches, for instance [16] and [17], use constraint logic programming to identify and address adverse interactions between actions. In this solution, a constraint logic programming (CLP) model is derived from the combination of logical models that represent the CIGs, then a mitigation algorithm is applied to detect and mitigate interactions. On the other hand, Sánchez-Garzón et al. [18] propose an agent-based approach to guideline merging. Each guideline, considered as a physician expert in the treatment of a single disease, is represented by an agent with hierarchical planning capabilities. The result is obtained through the coordination of all the agents and respects the recommendations of each guideline. Riaño et al. represent guidelines as sets of clinical actions that are modelled into an ontology [19]. To combine two treatments, first they are unified in a unique treatment and then a set of “combination

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2 Notice that the absence of certain part in the Reducing metabolism effect is given by the uncertainty in the execution of E1. Indeed, constraining, for instance, E1 to be executed on day ‘1’ would produce a different minimal network in which the effect certainly occurs on days ‘2’ and ‘3’. In such a case, the answer of the system would be “YES” and the overlap of the certain parts would be evident from the graphical representation.
rules” is applied to detect and avoid possible interactions. A model-based automatic merge of CIGs is then proposed in [20] through the definition of a combining operator.

In general, all the approaches coping with comorbidities in literature do not consider time, or consider it in a very marginal way. However, temporal issues are pervasive in the CIG context, and many previous approaches have faced some of them (see, e.g., the survey in [5]). The approach in this paper is the first one that deeply takes into account the temporal dimension in the treatment of comorbid patients. This is, in our opinion, a crucial advance with respect to the state of the art: a non-temporal analysis can only consider theoretically possible interactions between actions (e.g., conflicts between their goals or effects) in different CIGs, while actual interactions occur in time, i.e., just in case that the considered goals or effects overlap in time. In this sense, we believe that our approach is somehow complementary with respect to the other approaches, so that an integration with some of them can be devised as a future work. Moreover, to devise an approach useful in practice, we aim at improving our methodology by extending it to manage inconsistencies between log and CIG constraints (e.g., through conformance analysis techniques). In addition, to return suitable results to physicians, also the possibility of recognize relevant interactions (exploiting, e.g., knowledge regarding the probability or the seriousness of interactions) would be useful. Finally, we plan to perform an extensive evaluation on real world cases and involving real users to validate our work.

6. REFERENCES