A Comprehensive Clinical Guideline Model and a Reasoning Mechanism for AAL Systems

Tiago Oliveira[1], **Ângelo Costa**[1], **José Neves**[1] and **Paulo Novais**[1]

[1]CCTC/Department of Informatics, University of Minho,
Braga (Portugal);
Email : {toliveira, acosta, pjon, jneves}@di.uminho.pt

ABSTRACT

The progressive ageing of population combined with the need for comfort in situations of disease and disability are pushing healthcare organizations and governments to find new solutions to enable people to live longer in their preferred environment, while having access to quality healthcare services. iGenda is an Ambient Assisted Living platform that provides constant monitoring to people with this type of needs. The use of a Computer-Interpretable Guideline model for decision making is one of the features of this platform. The model used to represent Clinical Practice Guidelines gathers a set of features that make guidelines more dynamic and easily implementable. The model is defined using Ontology Web Language, profiting from the existing constructors provided by this language. It is based on a set of primitive tasks, namely Plans, Actions, Questions and Decisions. Focusing on decision support, a method for dealing with incomplete information about the clinical parameters of a health record is presented. The objective is to keep a continuous flow of information through the decision process and assuring that an outcome is always achieved. The usefulness of the integration of guideline recommendations with a reason mechanism capable of handling incomplete information is demonstrated through a case study about the diagnosis of metabolic syndrome.

Keywords: Ambient Assisted Living, Clinical Practice Guidelines, Computer-Interpretable Guidelines, Knowledge Representation, Incomplete Information, Decision Support.

Mathematics Subject Classification: 68T37, 68T30, 68N17.

1. Introduction

The increase in life expectancy and the decrease in fertility are ageing the population of developed countries. This tendency is evident when one analyses the statistical data of the 27 countries of the European Union. In 2008, the percentage of population with more than 65 years old was already 17% and predictions for the year 2060 point to a number of 60% (Giannakouris, 2008). When considering population with more than 85 years old, the estimated increase will be from 4% to 12% (Giannakouris, 2008). As people grow old they become progressively more ill and debilitated. Hence they require more care and medical attention, which usually come at a great economic cost. The dilemma that governments are facing is the establishment of equilibrium between providing appropriate care to their population and reducing overall spending. By living longer, people create the need for the development of a healthcare model that provides a fast response to any adverse situation. This may only be accomplished through the constant monitoring of their daily life activities and investment in prevention rather than in *a posteriori* treatment which is frequently more costly.

Ambient Assisted Living (AAL), a relatively recent field in Artificial Intelligence (AI) (Aarts et al., 2011; Novais et al., 2010) (), may provide the means to implement such a healthcare model. The goal of

AAL is to apply ambient intelligence technology to enable people with specific demands (e.g., people with physical/cognitive disabilities, elderly people) to live in their preferred environment longer (Nehmer et al., 2006; Tazari et al., 2011). iGenda is a platform that embodies this purpose (Costa et al., 2012). It is the result of the combination of two key concepts: intelligent agenda management and intelligent monitoring. This platform uses Clinical Practice Guidelines (CPGs) (Rosenbrand et al., 2008) in a machine readable format to provide decision support when scheduling activities and issuing alerts to healthcare professionals. Through the use of CPGs it is possible to detect some adverse situation concerning the elderly person's health condition. CPGs are systematically developed documents, based on scientific evidence and consensus among experts that provide recommendations to deal with specific clinical circumstances (Qaseem et al., 2007; Rosenbrand et al., 2008). iGenda also uses a method based on Extended Logic Programming (ELP) (Neves et al., 2012; Novais et al., 2010) to manage incomplete information about the health condition of a person. This method is useful to enable the system to reason about missing, inexact and conflicting information.

This paper presents the Computer-Interpretable Guideline (CIG) model (Oliveira et al., 2012) used in iGenda as well as the reasoning mechanism used to deal with incomplete information. Section two makes a brief description of the iGenda platform, its architecture and overall functionalities. In section three, some existing CIG models are presented in order to contextualize this new approach in the current state of the art. The proposed CIG model is described in section four along with a guideline example. Section five describes the reasoning mechanism that integrates guideline recommendations and a person's health condition. The last section of the paper draws conclusions about the implementation of the CIG model and ELP in the monitoring system.

2. The iGenda Platform

iGenda is a multi-agent system (Carneiro et al., 2010) that has the primary objective of providing an immediate response to problems through the use of mobile and static sensors (Costa et al., 2012). This system presents a hybrid architecture, in terms of multi-agent systems, where there are sets of agents distributed among a layered structure. The system operates at three levels: data acquisition and processing; activity detection; scheduling and decision making. These levels are depicted in Figure 1 along with the main modules that compose them.

The data acquisition and processing level is based on a sensor network comprised of static and mobile sensors (Costa et al., 2012). The static sensors are mainly video cameras that capture images for posterior shape interpretation and recognition. The monitoring capabilities also involve movement, object placement, temperature and vital signs, among others. These parameters are obtained through mobile sensors integrated in a mobile platform in order for iGenda to be available anywhere anytime. The combination between mobile based and desktop platforms assures availability and data capture. Moreover, mobile devices, like smartphones, have interesting built-in sensors such as accelerometers, luminosity sensors and global positioning system (GPS). Since a smartphone is a device carried by a person at all times, it is possible, through the use of these sensors, to enable fall detection functionalities or even further characterization of human movement for monitoring physical exercise (Costa et al., 2012). The sensor network also encompasses other forms of medical detection, namely

electrocardiogram (ECG), blood pressure and pulse oximetry. This level of the system manages the information and gathers it to build a health record in order to feed relevant information to the levels above.

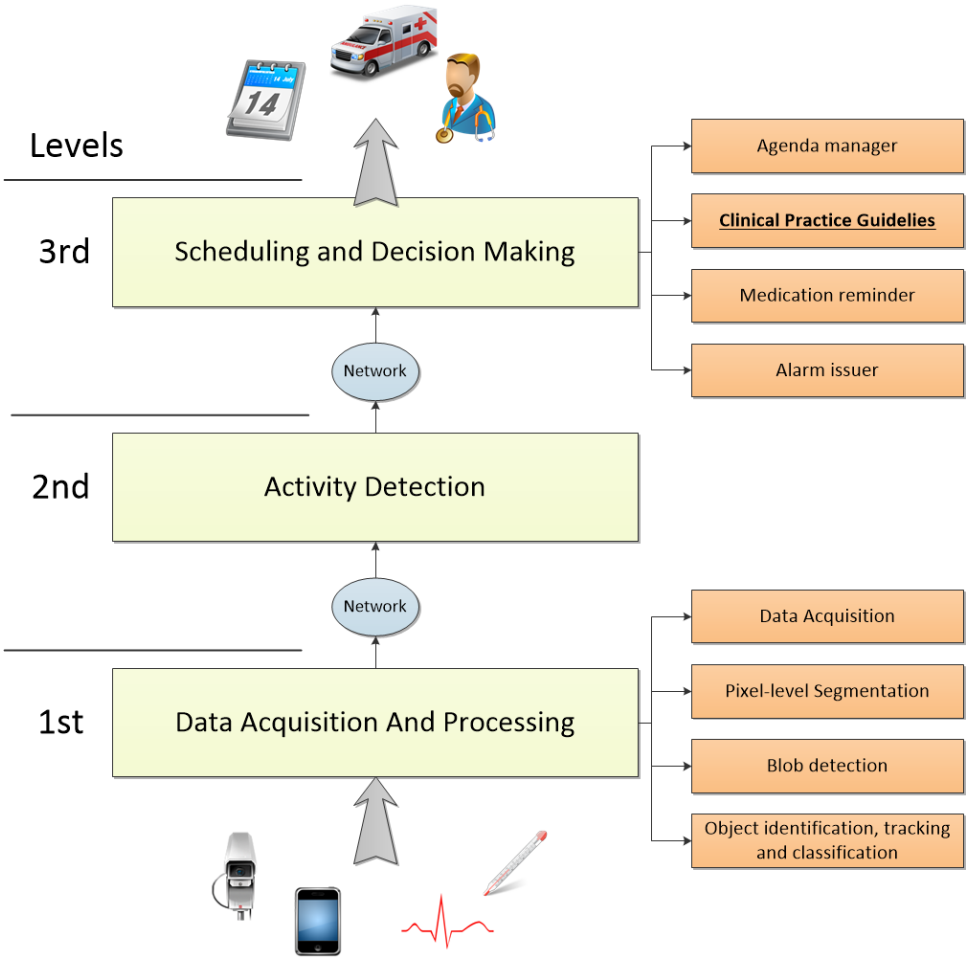

Figure 1. The modules of the iGenda platform.

As it may be seen in Figure 1 the modules available in the data acquisition and processing level include different data acquisition, image processing and tracking components, as well as an interface for the user to insert specific health parameters.

The activity detection level is in charge of recognising human activities through an algorithm that incorporates external knowledge about the domain, namely activity patterns. The algorithm works with shape and trajectory to indicate events related with moving objects. Monitoring physical exercise and fall detection occur at this level. In a specific scenario, the system constructs a state diagram that describes the activities of a person at a given moment.

The scheduling and decision making level is the highest of the three. It receives data from the other levels through communication protocols, namely Simple Object Access Protocol (SOAP) (Box et al., 2000). This level is responsible for intelligent scheduling with several events in charge of actions such

as taking medication, appointing consultations with physicians or scheduling exercise programs. The activities are inserted in the free slots of the calendar according to the outcome of a decision engine that verifies if there are conflicts and solves them in the best possible way. This level is also in charge of issuing reminders with health recommendations to the user and alarms to the physician if his health condition requires it. To decide which events to schedule or when to issue a reminder/recommendation, the system relies, among other things, on machine readable versions of CPGs. The execution engine for CPGs of the scheduling and decision making level provides services to help the diagnosis and follow-up of health problems

3. Approaches to Computer-Interpretable Guidelines

The first approach to CIG modelling, although rudimentary, was implemented in the HELP system (Gardner et al., 1999). This system was initially tested at the LDS Hospital, in Salt Lake City, in the United States (US). It became operational in 1967, maintaining this status until today. The guideline modelling component of the system consists in a set of modules, known as *Help Sectors* that contain the clinical knowledge in the form of logical rules. However, it was not until the end of the 1980s that CIG development started to proliferate and important models such as Arden Syntax, GLIF3, Asbru, PROforma, GUIDE and SAGE appeared.

Arden Syntax (Samwald et al., 2012) was one of the early approaches. It sets guidelines as independent modules. This model was first presented in 1989 and since then became one of the standards of Health Level Seven (HL7). The structure of a CPG in Arden syntax is called *Medical Logic Module* (MLM) Each MLM is divided in three layers that comprise different types of information. The clinical knowledge is inside the *Knowledge layer* in the form of if-then-else rules related to the clinical parameters of the patient. This is the main compartment of a MLM and contains information for only one decision in the clinical workflow. Administrative information (e.g., authoring, purpose) about the guideline is kept in the *Administrative layer* and information concerning the updates and versions of the guideline is kept under the *Maintenance layer*. A MLM is a simple text file using a syntax described in Backus-Naur Form (BNF).

Another important approach is GLIF (Patel et al, 1998). It uses a Task Network Model (TNM) approach to CPGs that comprises a set of steps that reflect the different moments of the clinical process. It was developed by the collaboration between Columbia, Harvard, and Stanford Universities. The current version of GLIF is GLIF3 (Peleg et al., 2000) and the types of steps described in the model are: *Decision*, *Patient State*, *Action*, *Synchronization* and *Branch*. *Decision*, *Patient State* and *Action* steps are used to represent decision points based on the condition of the patient, data entry points in the clinical workflow and clinical procedures, respectively. *Branch* and *Synchronization* are used to represent steps that must be executed simultaneously and the reunification of the workflow after their execution.

Asbru (Shahar et al., 1998) was developed at Stanford and Vienna Universities and it is primarily focused on temporal aspects of CPG appliance. Guidelines are represented as plans with complex temporal patterns and annotations. Plans are collections of items. The knowledge necessary to execute a task is contained in *Knowledge Roles*. The *Knowledge Roles* defined in Asbru are

Preferences, *Plan Intentions*, *Conditions* and *Effect*s. Among the tools to execute and construct guidelines in Asbru, the AsbruView (Miksch et al, 1998) and DeGeL (Shahar et al., 2003) are the ones to be pointed out. The core feature of AsbruView is a temporal view of the patient's state, with the different temporal constraints in display. DeGel is oriented to obtain CPGs from formal textual documents. The initial textual guidelines go through intermediate layers between the original form and the Asbru form, through which the system adds semantic content.

GUIDE (Ciccarese et al., 2003) is the depiction model used in the in the NewGuide framework for modelling and implementing CPGs. It was developed at the University of Pavia in Italy and it is based on petri nets, since they provide easy ways of modelling concurrent processes and temporal data. Medical terms are described using the Unified Medical Language System (UMLS) codification and clinical interventions are described through the Guideline text Mark-up, a Text Mark-up Language.

SAGE (Tu et al., 2007) is a project currently in development by a group of organizations that includes the Stanford Medical Informatics and the Mayo Clinic. The primary objective of this project is the establishment of a framework for acquiring and sharing guidelines in multiple healthcare systems. SAGE applies the EON model for the formalization of CPGs. SAGE presents a view of CPGs as *Recommendation Sets*, represented as a graph of *Context Nodes*. Each node is an instance of one of three classes: *Action*, *Decision* and *Routing*. This project includes a guideline execution engine that retrieves the patient's state from the electronic health record of the healthcare institution. SAGE uses standard terminologies, such as SNOMED-CT (Cornet & Schulz, 2009) and LOINC (Dugas et al., 2009), to provide unequivocal meaning to clinical terms.

None of the above mentioned models has a wide practical implementation. They are usually criticized for having too much or too little complexity and thus not being able to provide appropriate constructors for the different types of information in CPGs. Moreover, some of them require proficiency in some programming languages to express logical rules or temporal constraints, which is impractical for healthcare professionals. The existing software tools for the different models usually do not provide an intuitive environment for healthcare professionals to construct and deploy CPGs as well as effective reasoning mechanisms to deal with incomplete information.

4. Clinical Practice Guideline Model for iGenda

The development of a machine-interpretable model for CPGs requires a special consideration for different types of information in order for it to be sufficiently expressive. As so, different types of primitives and properties have to be defined to act as the basic building blocks of CPGs.

4.1. Requirements for the Computer-Interpretable Guideline Model

Most research studies consider that the TNM approach is the most suitable for a CIG model (Wang et al., 2002). The representation of CPGs as sets of different types of tasks assures the construction of a workflow of procedures that must be carried out in order to conduct a clinical process. The definition of different types of tasks is important since the activities of healthcare professionals are oriented by different types of clinical objectives.

The model should also provide attributes for the establishment of an order between the different tasks (Isern & Moreno, 2008). The execution of tasks may not be sequential. Some of them may represent procedures of a treatment that requires their simultaneous deployment. Moreover, the opposite situation may occur when, as result of a decision moment, a task should be executed instead of another. Parallel and concurrent executions of procedures are common in clinical processes and should, therefore, be included in a CIG model. Other constraints to the execution of tasks include temporal and clinical constraints (Wang et al., 2002). Temporal constraints are extremely important, partly because healthcare professionals always assess a person's health condition taking into account the time at which the clinical parameters were retrieved, but mostly because the recommendations of CPGs normally contain specifications about their intended duration, number of repetitions and periodicity. Besides having these temporal specifications, CPG recommendations also have a set of different conditions that restrain their appliance. For instance, pre-conditions are normally used to verify if the requirements for the execution of a task are gathered, an example is the verification if a person is allergic to some type of substance when administering or prescribing medication. Other clinical constraints to the execution of tasks are the expected outcomes. Even if there are some temporal restrictions to recommendations, usually they are oriented towards achieving a certain clinical goal and they end only when that goal is accomplished. There are other situations in which a recommendation is provided based on the occurrence of events related with a person's health condition, it may happen when a given clinical parameter rises above a predetermined threshold or when a healthcare professional reaches a conclusion and inserts it in the system. These events are called trigger conditions and their inclusion in a CIG model will make it more dynamic and intuitive.

The decision is a crucial moment in the clinical process and CPGs provide not only the steps that must occur before it (for preparation) but also the rules for the decision process to take place. Formally, a rule is viewed as a statement that may be divided in two parts: premises and conclusion. The premises express conditions that must hold true in order to inference the corresponding conclusion, in a *modus ponens* argument form. On the other hand, the conclusion is one of the options available during a decision, so each option of a decision process is associated with a set of rules that determine its selection.

The reuse of knowledge is also an important part of the model. This means that it should be possible to isolate modules of knowledge of a guideline and reuse them in another guideline that has those segments in common. In fact, it should not be necessary to insert repeated knowledge in the system, since the model should provide mechanisms to reference a guideline inside another one. This is an important issue that the available CIG approaches not always address.

4.2. Representation Primitives and Properties

Taking into consideration the requirements presented in the previous section, the following model has the objective of accommodating any clinical workflow. To do so, the model should be generic in order to adapt to the context and necessities of different guidelines and, at the same time, allow the definition of constraints characteristic of clinical workflows.

Every step described in a CPG is modelled as a task displayed in an oriented graph (Oliveira et al., 2012). The task is the basic unit of the model and there are different representation primitives that define the four basic tasks: *Plan*, *Action*, *Question* and *Decision*. Figure 2 shows the main components of the model along with the representation primitives. It was defined using Ontology Web Language (OWL) (W3C, 2009). The reason for choosing this ontology representation language was the formal semantics that it provides, which facilitates greater machine interpretability. OWL has three basic constructs:

- *Class*: a group of individuals that belong together because they share some properties;
- *Property*: a statement of a relationship between individuals or a relationship between individuals and data; and
- *Individual*: an instance of a class. Properties may be used to relate one individual to another.

In Figure 2 only the top classes of the model are displayed. Any class defined in OWL is a subclass of a more generic one called *Thing*. As such, the individuals that belong to the class *ClinicalPracticeGuideline* are instances of CPGs.

In this model, a guideline is viewed as a collection of tasks called *Plan*. This is the reason for the existence of the object property *hasPlan* linking individuals from *ClinicalPracticeGuideline* to it. *A Plan* is a subclass of *ClinicalTask* and it is a composite task which means that it may include any number of instances of the other classes of atomic tasks, such as *Action*, *Decision* and *Question*. A *Plan*'s first task is linked to it through the *hasFirstTask* object property and then the following tasks are linked to the previous by the *hasNextTask* property, in a way similar to a linked list. Figure 2 shows that a *Plan* may also be linked to the other tasks through *hasNextTask* which means that this class main contain another instance of itself in its task collection. This addresses one of the essential requirements of CIG models, nesting. Nesting permits the reference to a *Plan* inside another and thus the reuse of existing knowledge components.

The *Action* clinical task represents a step that must be performed by a healthcare agent (either a human or an intelligent artificial agent) towards the person to whom the guideline execution is oriented. The scope of this task includes clinical procedures, clinical exams, observations and recommendations. The recommendations may be of two types: a medication or a non-medication recommendation. The instances of an *Action* class possess data properties for their detailed description and are linked by object properties to the individuals of *ClinicalActionType* which define the different clinical actions that this representation primitive may refer to.

To express decision moments in the workflow the model provides a *Decision* task. It is a bifurcation point in the guideline execution process and requires the choice between two or more options. These options are associated with rules that have premises related with the health condition of the person being monitored. The options and rules are defined by linking the individuals of *Decision* to the individuals of *ClinicalConstraintElement* subclasses. These subclasses provide the basic constructs to define conditions and comparison operators such as >, <, =, ≥ and ≤, in order to facilitate reasoning with the clinical parameters.

The *Question* class is the last of the task primitives. It is used to obtain information about a person's health condition, more specifically about the values of the clinical parameters necessary to execute

the guideline. Each question possesses data attributes that specify what clinical parameters are necessary, the type of value that should be inserted (qualitative or quantitative) and the unit in which the values should be expressed. The *ConstraintElement* class also provides subclasses to express the pre-conditions and outcomes of the clinical tasks. Moreover, it enables the definition of trigger conditions. These trigger conditions are important after a *Decision* task since the outcome of the decision process will act as the trigger of the guideline's next task. In this situation there is always an instance of the *Alternative* class, which determines that in that point a choice must occur between two or more tasks. The tasks referenced by the *Alternative* instance have as trigger conditions the options available at the *Decision* that preceded them. The other class in *ExecutionType*, *Parallel*, is meant to reference tasks that must be executed simultaneously

Finally, *TemporalElement* provides the constructors to define duration, loops and periodicity of tasks along with temporal units and temporal operators.

To better understand how a CPG looks like when it is represented in this model, Figure 3 presents a case study related with a guideline for the Detection, Evaluation and Treatment of High Blood Cholesterol in Adults (National Heart Lung and Blood Institute, 2002), developed by the National Heart Lung and Blood Institute (NHLBI) of the US. The development of this case study consisted in selecting a set of recommendations from the guideline and assessing if it was possible to represent them with the CIG model proposed in this paper.

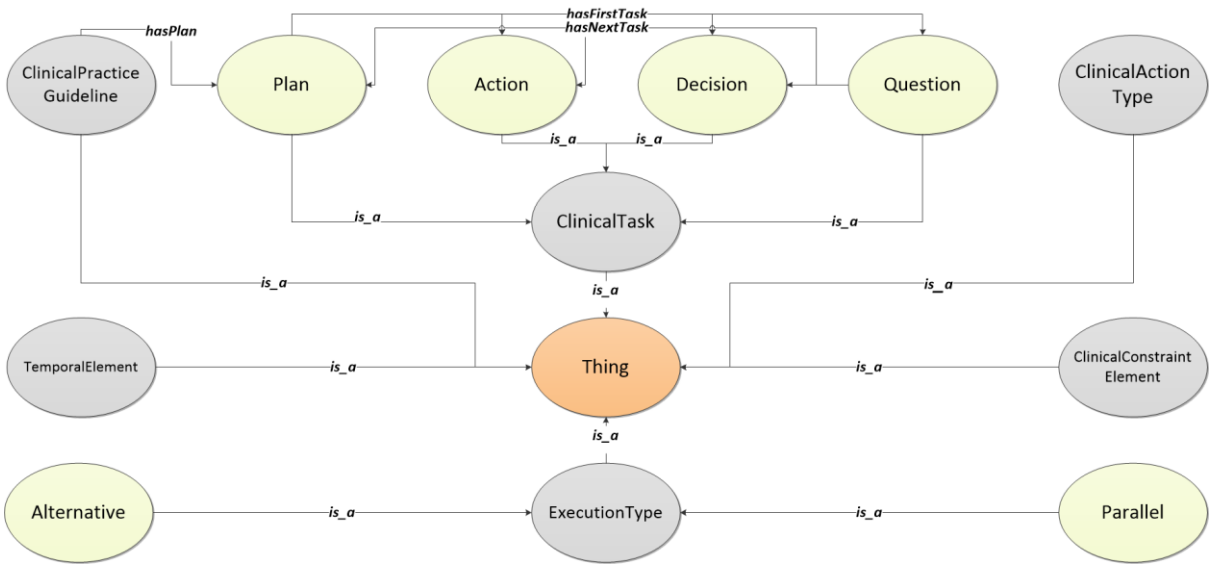

Figure 2. The main classes of the proposed CIG model for iGenda.

The set of instructions that was selected refers to the diagnostic of metabolic syndrome, which is a combination of medical disorders that, when occurring together, increase the risk of developing cardiovascular disease (National Heart Lung and Blood Institute, 2002). The purpose is to demonstrate how the main primitive classes presented above should be used. This CPG is very

useful for monitoring purposes since it manages clinical parameters and a health condition that are very common in older adults.

The CPG is represented as an instance of the *ClinicalPracticeGuideline* class with the name data property. The whole set is represented as tasks inside a composite task, a *Plan*, with the name Detection of High Blood Cholesterol in Children and Adults associated with the term cholesterol. The careflow starts with a *Question* task with the objective of acquiring the values of the following clinical parameters: fasting glucose, triglycerides and waist circumference. These are the parameters required for the diagnostic of metabolic syndrome. The values of these parameters should be obtained from the inputs of the person being monitored or the healthcare professional in charge and once they are asserted to the health record, the next task, which is a *Decision*, is performed. This *Decision* task has the objective of diagnosing metabolic syndrome. To do so, the options are available as instances of subclasses of *ClinicalConstraintElement* along with the rules that determine their selection, linked to the *Decision* by an object property. After the *Decision* task comes an instance of the *Alternative* class that expresses a bifurcation in the careflow. There are two *Action* tasks that are mutually exclusive and have different trigger conditions, each one of them matching the options available at the *Decision*. Both Actions have a general description and are linked to individuals of *ClinicalActionType* that specify what kind of activity must take place. The non-medication recommendation advising moderate physical activity is bound by temporal constraints in the form of instances of *TemporalElement*. If this task happens to be selected by the decision making module of iGenda, the agenda manager can extract these temporal constraints and schedule the physical activity in the calendar of the person being monitored, according to the duration and periodicity specified.

5. Incomplete Information

Incomplete information is a problem that affects many decision support and monitoring systems, especially in the clinical domain, as it is evidenced in (Straszecka, 2006). Under the scope of this term, one may include missing, conflicting and incoherent information, all of which have the potential of disrupting the flow of information in any decision making process. This paper presents a model that, in terms of knowledge representation, provides sufficiently expressive constructs to handle such cases, along with a confidence value that provides a measure of the availability of the information.

The model used in iGenda to deal with this type of information is based on ELP (Novais et al., 2010; Neves et al., 2012). To fit this representation formalism, a punctuation system called Quality-of-Information (QoI) (Neves et al., 2012; Novais et al., 2010) was developed.

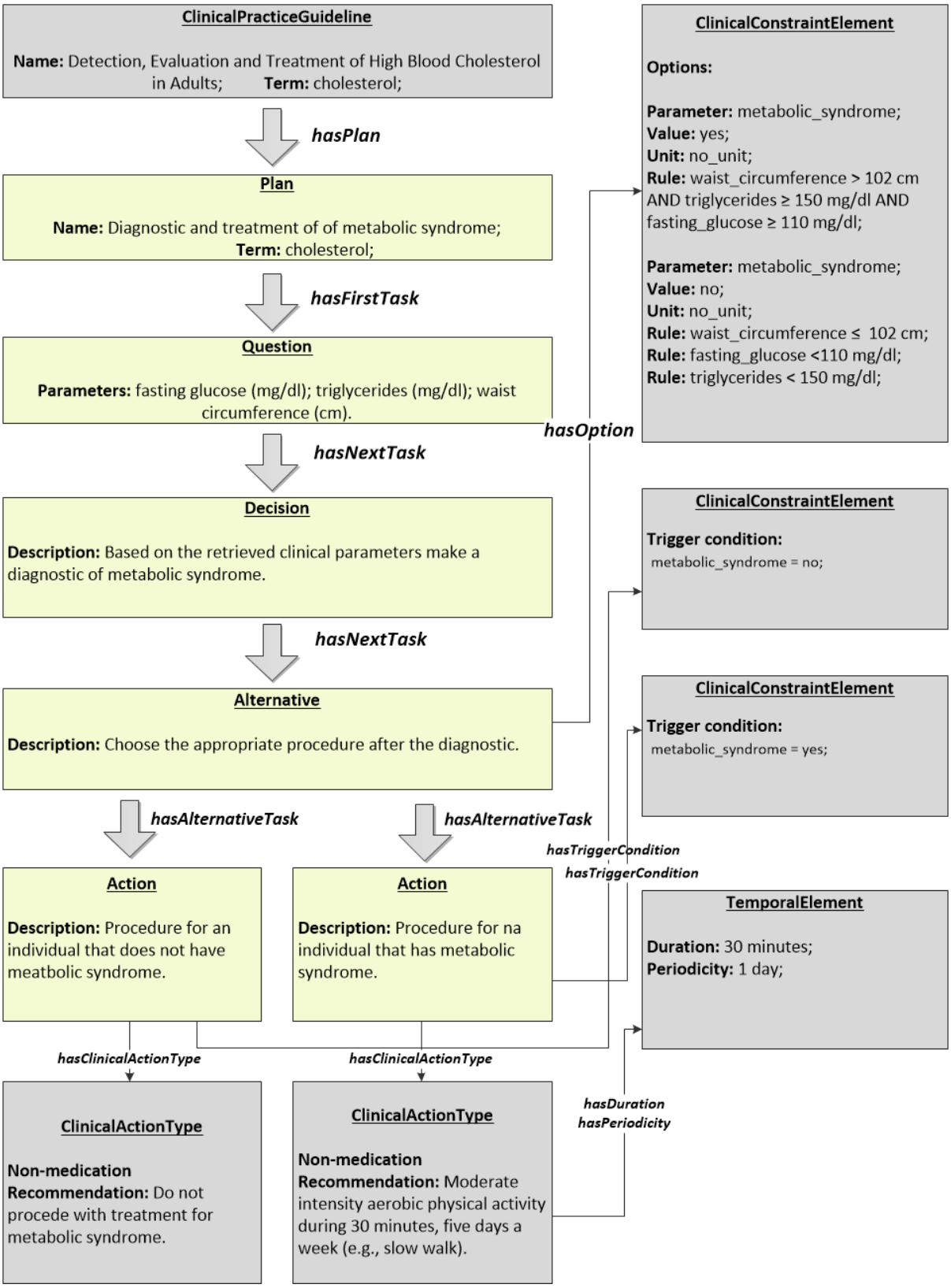

Figure 3. Case-study of a CPG represented in the CIG model of iGenda.

5.1. Extended Logic Programing

The representation of the retrieved parameters from the individuals being monitored is done using ELP. This formalism uses classic negation (*not p*) and default negation (*¬ p*), as established in (Novais et al., 2010; Neves et al., 2012), representing the cases of incomplete information as abducible sets of the predicates extension that refer to the parameters in question. Every ELP program is composed of a finite set of clauses in the form:

$q \leftarrow p_1 \wedge \ldots \wedge p_n \wedge not\ q_1 \wedge \ldots \wedge not\ q_m.$
$? \ p_1 \wedge \ldots \wedge p_n \wedge not\ q_1 \wedge \ldots \wedge not\ q_m \ (n, m \geq 0) \ .$

The symbol *?* is a domain atom representing falsity and p_i, q_i are classical ground literals. ELP introduces a new truth value, besides the ordinary true or false. Unknown becomes a possible value for a case of incomplete information, as it is evident in the procedure *demo*, a meta predicate that defines the truth values of an ELP program:

demo(T, true) ← *T.*
demo(T, false) ← *¬ T.*
demo(T, unknown) ← *not T, not ¬ T.*

Let us consider the cases of two individuals, A and B. Concerning individual A, it is known that the level of triglycerides is exactly 155 mg/dl, but there are imprecise values for the waist circumference and fasting glucose. The waist circumference of individual A is either 100 or 103 cm, as a result of two measurements performed one after another. This could be due to the healthcare professional not following the right procedure for measuring the waist circumference in one of the measurements. The fasting glucose level is also uncertain, but believed to be in the set 107 and 111 mg/dl. Fasting glucose is a level that shifts quickly between measurements, so if a second measurement is done to be sure of the value of the first one, there is a high probability of the value being different. As for individual B, the value for the waist circumference is 104 cm and the value for fasting glucose is 115 mg/dl, but there is no information about the level of triglycerides.
Programs 1 and 2 reflect the extension of the predicates in ELP that symbolize these clinical parameters for individuals A and B respectively.

Program 1. Extensions of predicates for the clinical parameters fasting glucose, triglycerides and waist circumference for individual A.

$\neg fasting\_glucose(X,Y) \leftarrow not\ \ fasting\_glucose(X,Y),\ not\ abducible_{fasting\_glucose}(X,Y).$
$abducible_{fasting\_glucose}(X,Y) \leftarrow fasting\_glucose(\perp,Y).$
$abducible_{fasting\_glucose}(107,mg/dl).$
$abducible_{fasting\_glucose}(111,mg/dl).$

¬ $triglycerides(X,Y) \leftarrow not\ \ triglycerides(X,Y), not\ abducible_{triglycerides\ (}X,Y).$
$abducible_{triglycerides}(X,Y) \leftarrow triglycerides(\perp,Y).$
$?((\ abducible_{triglycerides}(X_1,Y_1) \vee abducible_{triglycerides}(X_2,\ Y_2))$
$\wedge\ (abducible_{triglycerides}(X_1,Y_1) \wedge abducible_{triglycerides}(X_2,\ Y_2)\ )).$
$triglycerides(155,mg/dl).$

¬ $waist\_circumference(X,Y) \leftarrow not\ \ waist\_circumference(X,Y), not\ abducible_{waist\_circumference}(X,Y).$
$abducible_{waist\_circumference}(X,Y) \leftarrow waist\_circumference\ (\perp,Y).$
$?((\ abducible_{waist\_circumference}(X_1,Y_1) \vee abducible_{waist\_circumference}(\ (X_2,\ Y_2))$
$\wedge\ (abducible_{waist\_circumference}(\ (X_1,Y_1) \wedge abducible_{waist\_circumference}(\ (X_2,\ Y_2)\ )).$
$abducible_{waist\_circumference}(100,cm).$
$abducible_{waist\_circumference}(103,cm).$

Program 2. Extensions of predicates for the clinical parameters fasting glucose, triglycerides and waist circumference for individual B.

¬$fasting\_glucose(X,Y) \leftarrow not\ \ fasting\_glucose(X,Y), not\ abducible_{fasting\_glucose}\ (X,Y).$
$abducible_{fasting\_glucose}(X,Y) \leftarrow fasting\_glucose(\perp,Y).$
$fasting\_glucose\ (115,mg/dl).$

$triglycerides(X,Y) \leftarrow not\ \ triglycerides(X,Y), not\ abducible_{triglycerides}\ (X,Y).$
$abducible_{triglycerides}(X,Y) \leftarrow triglycerides(\perp,Y).$
$?((\ abducible_{triglycerides}(X_1,Y_1) \vee abducible_{triglycerides}(X_2,\ Y_2))$
$\wedge\ (abducible_{triglycerides}(X_1,Y_1) \wedge abducible_{triglycerides}(X_2,\ Y_2)\ )).$
$triglycerides(\perp,mg/dl).$

¬ $waist\_circumference(X,Y) \leftarrow not\ \ waist\_circumference(X,Y), not\ abducible_{waist\_circumference}(X,Y).$
$abducible_{waist\_circumference}(X,Y) \leftarrow waist\_circumference(\perp,Y).$
$?((\ abducible_{waist\_circumferenc}e(X_1,Y_1) \vee abducible_{waist\_circumference}(\ (X_2,\ Y_2))$
$\wedge\ (abducible_{waist\_circumference}(\ (X_1,Y_1) \wedge abducible_{waist\_circumference(}\ (X_2,\ Y_2)\ )).$
$waist\_circumference(104,cm).$

In both programs, the first clause of each extension defines their closure, i.e., the application of the closed world assumption, meaning that a statement is considered to be false if it is represented neither as positive information in the knowledge base nor as an abducible statement. The second clause of each predicate denotes that a value is abducible if it is represented as positive information with the logical symbol $\perp$. When this happens, the program interprets it as an abducible that may assume any value of the domain.

It is possible for a health parameter to assume more than a value of its set of abducibles in an information scenario. This is the case for fasting glucose, since it is a blood level that shifts quickly between measurements. Therefore, it is associated with a higher degree of uncertainty. For parameters that do not fit this case, an invariant is added to the extension of their predicates, expressed by the third clause of parameters triglycerides and waist circumference.

The model involves the generation of information scenarios by combining the different abducible sets, thus creating different states of information. The information scenarios generated for these two cases are displayed in Table 1.

5.2. Quality-of-Information and Health Condition Scores

In each information scenario the model resorts to the QoI (Novais et al., 2010; Neves et al., 2012) which represents a truth value of the extension of a predicate/parameter *i*. This value is in the closed interval [0,1] with 0 being the QoI for false (negative) information and 1 being the QoI for positive known information. It provides a measure of the reliability of the information. If the information is unknown, the QoI is calculated through Equation 1, where the *N* stands for the number of possible values for the parameter in the domain

$$QoI_i = \lim_{N \to \infty} 1/N = 0 (N >> 0) \qquad (1)$$

However, if there is a finite set of abducibles for the extension of *i*, the *QoI* may be calculated in two distinct ways. If the predicate/parameter has an invariant expressing the mutual exclusivity of its values, the QoI is given by Equation 2, where *Card* denotes the number of abducibles. If this is not the case, the value of *i* may assume any number of combinations of its abducibles in a scenario, a situation expressed by Equation 3.

$$QoI_i = 1/Card \qquad (2)$$

$$QoI_i = 1/(C_1^{Card} + \ldots + C_{Card}^{Card}) = 1/(\sum_{j=0}^{Card} C_j^{Card} - 1) = 1/(2^{Card} - 1) \qquad (3)$$

The scheduling and decision making module of iGenda uses an inference engine to provide recommendations based on clinical guidelines, coded in OWL files. These guidelines contain the knowledge, in the form of rules that allow the platform to determine the health condition of an individual. Figure 2 shows an excerpt the guideline used in iGenda that suggests that this health condition encompasses a fasting glucose level higher or equal to 110 mg/dl, a triglycerides level higher or equal to 150 mg/dl and a waist circumference superior to 102 cm. If any of these conditions does not hold, it is considered that an individual does not have metabolic syndrome. For these situations, the model provides a scoring method for the options in consideration (V_{option}) during a *Decision*, based on the QoI of their conditions. So, a health parameter/predicate *k* has a relative weight in an option (w_k^{option}), according to the rule in which they appear (Equation 4), for a rule with *n* conditions. With the scoring function for an option (Equation 5), it is possible to rank the options according to their viability in each scenario and select the option with the highest rank.

Table 1. The information scenarios generated from programs 1 and 2 with their QoIs and scores.

	Information Scenarios	***QoI***	***Inferable Options***
From Program 1			
1	*¬fasting_glucose(QOI,X,Y) ← not fasting_glucose(QOI,X,Y).* *fasting_glucose(0.33,107,mg/dl).* *¬ triglycerides(QOI,X,Y) ← not triglycerides(QOI,X,Y).* *triglycerides(1,155,mg/dl).* *¬ waist_circumference(QOIX,Y) ← not waist_circumference(QOI,X,Y),* *waist_circumference(0.50,100,true,cm).*	$QoI_{fasting\_glucose}$= $1/(2^2-1)=0.33$ $QoI_{tryglicerides}=1$ $QoI_{waist\_circumference}=1/2=0.50$	$V_{metabolic\_syndrome\ -\ no}=0.33$ (from fasting glucose) $V_{metabolic\_syndrome\ -\ no}=0.50$ (from waist circumference)
2	*¬fasting_glucose(QOI,X,Y) ← not fasting_glucose(QOI,X,Y).* *fasting_glucose(0.33,107,mg/dl).* *¬ triglycerides (QOI,X,Y) ← not triglycerides(QOI,X,Y).* *triglycerides(1.000,155,mg/dl).* *¬ waist_circumference(QOI,X,Y) ← not waist_circumference(QOI,X,Y),* *waist_circumference(0.50,103,cm).*	$QoI_{fasting\_glucose}$= $1/(2^2-1)=0.33$ $QoI_{tryglicerides}$= 1 $QoI_{waist\_circumference}$= 1/2=0.50	$V_{metabolic\_syndrome\ -\ no}$ =0.33 (from fasting glucose)
3	*¬fasting_glucose(QOI,X,Y) ← not fasting_glucose(QOI,X,Y).* *fasting_glucose(0.33,111,mg/dl).* *¬ triglycerides(QOI,X,Y) ← not trygliceride(QOI,X,Y).* *triglycerides(1,155,mg/dl).* *¬ waist_circumference(QOIX,Y) ← not waist_circumference(QOI,X,Y),* *waist_circumference(0.50,100,true,cm).*	$QoI_{fasting\_glucose}$= $1/(2^2-1)=0.33$ $QoI_{tryglicerides}=1$ $QoI_{waist\_circumference}=1/2=0.50$	$V_{metabolic\_syndrome\ -\ no}$ =0.50 (from waist circumference)
4	*¬fasting_glucose(QOI,X,Y) ← not fasting_glucose(QOI,X,Y).* *fasting_glucose(0.33,111,mg/dl).* *¬ triglycerides(QOI,X,Y) ← not triglycerides(QOI,X,Y).* *triglycerides(1.000,155,mg/dl).* *¬ waist_circumference(QOI,X,Y) ← not waist_circumference(QOI,X,Y),* *waist_circumference(0.50,103,cm).*	$QoI_{fasting\_glucose}$= $1/(2^2-1)=0.33$ $QoI_{tryglicerides}=1$ $QoI_{waist\_circumference}=1/2=0.50$	$V_{metabolic\_syndrome\ -\ yes}$ =0.33*0.33+0.33*1+ 0.33*0.50= 0.60 (from all parameters)
5	*¬fasting_glucose(QOI,X,Y) ← not fasting_glucose(QOI,X,Y).* *fasting_glucose(0.17,107,mg/dl).* *fasting_glucose(0.17,111,mg/dl).* *¬ triglycerides(QOI,X,Y) ← not triglycerides(QOI,X,Y).* *triglycerides(1,155,mg/dl).* *¬ waist_circumference(QOIX,Y) ← not waist_circumference(QOI,X,Y),* *waist_circumference(0.50,100,true,cm).*	QoIfasting_glucose= $(1/(2^2-1))/2=0.17$ QoItrygliceride=1 QoIwaist_circumference= 1/2=0.50	$V_{metabolic\_syndrome\ -\ no}$=0.17 (from fasting glucose) $V_{metabolic\_syndrome\ -\ no}$=0.50 (from waist circumference)
6	*¬fasting_glucose(QOI,X,Y) ← not fasting_glucose(QOI,X,Y).* *fasting_glucose(0.17,107,mg/dl).* *fasting_glucose(0.17,111,mg/dl).* *¬ triglycerides(QOI,X,Y) ← not triglycerides(QOI,X,Y).* *trygliceride(1,155,mg/dl).* *¬ waist_circumference(QOIX,Y) ← not waist_circumference(QOI,X,Y),* *waist_circumference(0.50,103,true,cm).*	QoIfasting_glucose= $(1/(2^2-1))/2=0.17$ QoItrygliceride=1 QoIwaist_circumference= 1/2=0.50	$V_{metabolic\_syndrome\ -\ no}$=0.17 (from fasting glucose) $V_{metabolic\_syndrome\ –\ yes}$ =0.33*0.17+0.33*1+ 0.33*0.50= 0.55 (from all parameters)
From Program 2			
1	*¬fasting_glucose(QOI,X,Y) ← not fasting_glucose(QOI,X,Y).* *fasting_glucose(1,115,mg/dl).* *¬ triglycerides(QOI,X,Y) ← not triglycerides(QOI,X,Y).* *triglycerides (0,true,mg/dl).* *¬ waist_circumference(QOI,X,Y) ← not waist_circumference(QOI,X,Y),* *waist_circumference(1,104,cm).*	$QoI_{fasting\_glucose}$=1 $QoI_{tryglicerides}$= 0 $QoI_{waist\_circumference}$= 1	$V_{metabolic\_syndrome\ -\ yes}$ =0.33*1+0.33*0+ 0.33*1=0.66 (from all parameters) $V_{metabolic\_syndrome\ -\ no}$=0 (from triglycerides)

$$\sum_{1 \le k \le n} w_k^{option} = 1, \forall option \quad (4)$$

$$V_{option} = \sum_{1 \le k \le n} w_k^{option} \times QoI_k \quad (5)$$

The decision making module selects the parameters from the database, builds the logic programs and generates the different information scenarios. The results of this procedure are displayed in Table 1. Concerning individual A, the combination of the waist circumference hypotheses, ({100,103} cm), with the hypotheses of the fasting glucose abducible set ({107, 111, {107 and 111}} mg/dl) yields six possible information scenarios. The option with the highest score is having metabolic syndrome which corresponds to scenario 4. This will be the information scenario used by the system in the decision making process. As for individual B, there is only one scenario where the triglycerides level may assume any value, given the high degree of uncertainty associated with this parameter. As a consequence, there are two inferable options, being again metabolic syndrome the one with the highest scored.

The decision making module mimics a human decision making process, with an initial stage of formulation of hypotheses, comprised of a survey of the available options and the generation of the information scenarios. The following stage is voting and may be subdivided in the evaluation of conditions, to see what options hold true (from the rules), and the assessment of the QoI with the computation of scores. The next stage is the option selection, determined by the highest score of all scenarios. Finally, the task selection occurs by providing a recommendation to the user's agenda, according to the outcome of the decision, using iGenda. Taking into consideration the two cases that were addressed and the information generated by them, iGenda should schedule sessions of physical activities.

6. Conclusions

A CIG representation model such as the one presented above provides constructs to create structured CPGs. This format makes CPGs more dynamic since they can be updated more easily. It also enables the creation of modular knowledge components and thus their reuse in different guidelines. Since this is a machine readable format, an easier implementation is possible by embedding guideline execution engines in healthcare related systems. CPGs are instruments for the promotion of good clinical practices, advising patients and healthcare professionals about the optimal procedures in specific clinical circumstances. The idea is for iGenda to take advantage of this clinical validity and at the same time provide a platform for healthcare professionals to apply clinical guidelines in the daily life of their patients in order to have a positive impact in their well-being.

The knowledge representation model and reasoning mechanism presented deal with the different forms of incomplete information, keeping a continuous flow of information though de decision making process, assuring that the system always reaches an outcome. It is one of the valences of the iGenda

platform, since it handles problems of data integrity in a context that deals with clinical information, providing the user with metrics of the confidence in the available information.

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