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REGULAR PAPER

Using OWL ontologies for adaptive patient information modelling and preoperative clinical decision support

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Abstract We here present our research and experience regarding the design and implementation of a knowledge-based preoperative assessment decision support system. We discuss generic design considerations as well as the practical system implementation. We developed the system using semantic web technology, including modular ontologies developed in the OWL web ontology language, the OWL Java application programming interface and an automated logic reasoner. We discuss how the system enables to tailor patient information collection according to personalized medical context. The use of ontologies at the core of the system's architecture permits to efficiently manage a vast repository of preoperative assessment domain knowledge, including classification of surgical procedures, classification of morbidities and guidelines for routine preoperative tests. Logical inference on the domain knowledge according to individual patient's medical context enables personalized patients' reports consisting of a risk assessment and clinical recommendations such as relevant preoperative tests.

Keywords Clinical decision support systems · Preoperative assessment and screening · Knowledge representation and reasoning

1 Introduction

Health professionals working in secondary care typically work in a challenging, intellectually demanding, knowledge-intensive and sometime emotionally stressful environment.

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Clinical staff are often expected to work long shifts, to be able to carry on multiple and simultaneous tasks, and continuously comply with an increasing number of clinical and patient safety guidelines. Throughout their work, they are also expected to make optimum and efficient use of their experience, professional judgement and clinical knowledge in order to make appropriate decisions or reach correct diagnoses in the best interest of the patients. In this environment, mistakes will inevitably take place as the result of lack of concentration or negligence, errors of judgement, omissions or substitutions, the failure to properly disclose information at shift handovers, etc. Clinical mistakes can have dramatic consequences for all involved, patients, families and health professionals while even a small percentage of error overall can rapidly add to a staggering absolute amount of adverse events simply due to the large volume of people who come into contact with the health services. As a result of a renewed emphasis worldwide on patient safety within health services, there is a sustained and growing interest within the research community and the health services in developing and deploying computer-based decision support systems (CDSS) into routine use within secondary care in order to support health professionals in their daily tasks and activities.

Preoperative assessment is a generic clinical screening process intended to identify early on in a patient journey potential risks of complications during or after surgery. By its very nature, the clinical knowledge potentially relevant to preoperative assessment is immense.

In this article, we present our work on the development of a knowledge-based preoperative decision support system. We discuss the design choices and implementation challenges in developing a system capable of supporting health professionals in secondary care during the preoperative assessment of patient prior to elective surgery. We first review in Sect. 2 related work on medical decision support systems and background information on the preoperative assessment process. We then discuss in Sect. 3.1 design features of the system, including technology and specificity of the domain knowledge. Finally, we describe in more details certain aspects of the system implementation in Sect. 4 and conclude with some final remarks and future work.

2 Medical computer decision support systems and the preoperative assessment process

The majority of errors within health delivery systems are not necessarily due to human errors, but are rather often consequences of broader systemic flaws in the organization of processes and services [1]. Many of these can be traced back to inefficient patient information management. Some common issues include the following:

(i) information that was relevant and potentially available was not collected… (e.g. *failed to ask the patient, relatives or family doctor about medication or allergies…*)
(ii) information that was collected was not acted upon… (e.g. *the patient record shows that the patient had severe diabetes that would have increased cardiovascular risks, yet no further cardiovascular tests were ordered prior to surgery*).
(iii) information that was known was not shared to relevant staff… (e.g. *failure to fully disclose information at shift handovers*).
(iv) information that was unknown was not uncovered in time… *(had an electrocardiogram test been carried out, abnormal heartbeats could have been uncovered).*

In this article, we are particularly interested in discussing considerations directly related to the efficient management and usage of patient medical information.

2.1 Medical computer decision support systems

As previously suggested, many clinical errors are caused by structural issues within the organization of processes and services rather then human error alone. The potential benefits of integrating CDSSs [2–10] within work practices include the ability to:

(i) influence clinicians behaviour and reduce variability of outcomes across various health professionals and increase the standardization of processes towards evidence-based guidelines.
(ii) combine and synthesize complex-related pieces of information.
(iii) facilitate access to clinical information and reporting of results through greater accessibility of data and improved display of information (e.g. using graphs and charts…)
(iv) support the generation of patient-specific (medical history) and context-specific (e.g. according to morbidity, surgical intervention, local hospital rules, etc.) prompts and reminders.
(v) reduce medication adverse events with computer-assisted order entry through a reduction of misread manual writing, notifications of adverse interaction, allergies, etc.
(vi) identify patterns within the patient data that must be acted upon (e.g. abnormal or inconsistent findings, alerts, ordering of tests and further investigations, referral to specialist consultant…)
(vii) doing all of the above while preserving health professionals' independence and ability to tailor patient care according to individual circumstances, specific needs, availability of resources or other constraints.

If successfully embedded within routine work practices, CDSSs can become important process standardization and error-preventing tools. While CDSSs have generally proved reliable whenever rules and guidelines are clearly applicable, their record on emulating medical diagnosis is rather less obvious. This is due to the inherent difficulty and complexity in designing explicit conceptual models of the medical diagnosis thought process, except perhaps in the most straightforward cases, which would limit the usefulness of such systems.

CDSSs have other inherent limitations: recommendations issued by the systems can only be as good as the guidelines they model, and as a result, flaws in the guidelines will unfortunately be systematically reproduced in the output of the system [6]. Clinical knowledge is always limited or partial, and it is not unusual for certain guidelines to be revised or proved wrong. Ironically, in these situations, patients' health would actually benefit from errors of omissions that a CDSS would make less likely [7]. There is obviously little CDSS designers can do about this problem apart from updating the system whenever new guidelines are introduced or old ones revised.

In addition, there are also considerable issues around the integration of CDSSs, both at the system level [11] and at the work processes and work-flows level [12]. Despite these potential barriers, a number of systems have successively been deployed within the health services. Several systematic reviews [2–4,8–10] concluded that CDSSs had generally (although not always…) demonstrated some benefits on clinical behaviour, compliance and performance during clinical controlled trials, including drug dosing and prescribing systems, preventive care and other generic or disease-specific systems. Regarding patients outcomes, results are less clear cut, in part due to the sparsity of available studies in that respect. In contrast, these studies showed that diagnostic aids have generally demonstrated little benefit to clinical practice overall (see Taylor's insightful description of the issues surrounding health informatics for a potential explanation of the lack of successes of diagnostic aids in [13]).

2.2 Preoperative assessment

In the United Kingdom, a patient due to undergo surgery will typically be referred to a hospital by his family doctor and will then first get an appointment at an out-patient clinic at the hospital for initial screening. The patient will then undergo a preoperative assessment (PA) consisting of: answering a clinical questionnaire, generally followed by a physical examination, certain laboratory tests and possibly referral to a specialist consultant. Patient screening can be performed in a variety of settings: face to face consultations, paper-based questionnaires, on the telephone or through web-based forms on the internet.

García-Miguel et al. [14] define preoperative assessment as *"the clinical investigation that precedes anaesthesia for surgical or non-surgical procedures, and is the responsibility of the anaesthetist"*. The primary goal of PA is to maximize a patient's fitness for a (i.e. surgical) procedure by:

(i) ensuring that the patient is fully informed about the procedure and has provided informed consent.
(ii) identifying early in the patient's health pathway potential risks of perioperative (i.e. *during*) and postoperative complications due to pre-existing conditions (e.g. cardiovascular or respiratory conditions, chronic diseases, multiple comorbidities, previous adverse events, etc.).
(iii) requesting additional investigations (e.g. tests) or referral to a specialist.
(iv) taking steps to improve patient fitness (e.g. referral to family doctor for smoking cessation, weight loss, chronic disease control and management, etc.)
(v) allocating appropriate resources for the day of surgery (e.g. taking appropriate actions to deal with patient's allergies, booking specialist equipment or a bed in critical care unit, etc.).
(vi) considering alternatives to surgery when the risks of surgery are considered too high for the patient's safety.
(vii) reducing the overall risk of late surgery cancellation by ensuring that all feasible precautionary steps have been taken prior to surgery.

Due to the vast scope of preoperative assessment, the clinical domain knowledge potentially relevant for assessment is virtually limitless. For this reason, a generic PA has traditionally focused on identifying common allergies, cardiovascular and respiratory risks and pre-empting potential airway complications, such as difficult intubation during anaesthesia. Complex surgical procedures may require additional precautions or even have separate specific preoperative protocols.

3 A knowledge-based preoperative assessment system

3.1 System design considerations

In addition to general considerations relevant to all CDSSs reviewed in the previous section, this research project had several important specific requirements. During the design phase of the project, requirements identified included that the system:

(i) be capable of capturing highly specific patient medical information in a structured and coherent, yet flexible (i.e. *adaptive*) manner.
(ii) have the ability to use and combine heterogeneous sources of clinical information.

(iii) be capable of making useful inferences based on available evidence-based preoperative assessment medical knowledge.
(iv) provide context-specific explanations for these medical inferences, targeted at a variety of health professionals (i.e. nurse, doctor, anaesthetist).
(v) provide some level of transparency regarding the mechanisms for reaching previous medical inferences.
(vi) provide some mechanisms to conveniently update and maintain the system in the face of new requirements and advances in the availability of evidence-based medical knowledge.
(vii) being compatible with earlier versions of the system, including handling data from legacy patient databases while providing the same level of decision support.

In addition, to these requirements, the system was developed as part of a knowledge transfer programme between the medical informatics group of the University of Manchester and CIS-Informatics, a Scottish healthcare software provider specialized in anaesthesia information management systems.[1] Thus, an important consideration during the development process was that the application internal models needed to be interoperable with information models of legacy databases and earlier systems. In addition, the system architecture needed to be understood and maintained by developers experienced in object-oriented software engineering but not necessarily very familiar with more formal aspects of knowledge representation. Recent progresses in knowledge engineering and reasoning have permitted to address previous performance limitations issues associated with knowledge-based systems, and robust automated reasoning industrial applications are now feasible for wide-scale deployment [15–17].

3.2 System overview

Figure 1 gives an overview of the general principles behind the architecture of our knowledge-based preoperative decision support system. The system is composed of five main elements:

1. A patient preoperative medical history information collection module. This component can be designed to be adaptive to the medical context of the information collected for all new patients entered in the system (case 1.a.). The adaptive behaviour of the system is obtained by modelling medical relationships and dependencies in a questionnaire ontology [18,19]. For patients whose medical history is already stored in some legacy clinical databases (case 1.b.), the automatic generation of a medical history is obtained through a reverse-engineering mapping from the legacy database information model to the questionnaire ontology [20].
2. The previous steps result in the generation of a patient preoperative medical history representation in OWL [21]. There is an important distinction to be made regarding this patient history: some of the information will have been obtained from clinical sources (e.g. examination by nurse or doctor, preoperative tests, etc.) However, the information directly collected from the patient himself through the patient questionnaire is likely to be "coarse-grained", even if responding to the questionnaire is supervised by a preoperative nurse, as is usually the case. Consider the following examples to illustrate this last point: a patient may know that he has *"diabetes"* but may be unable to qualify his condition any further than this. He may know that he is taking medication for a

[1] http://www.informatics-cis.com/.

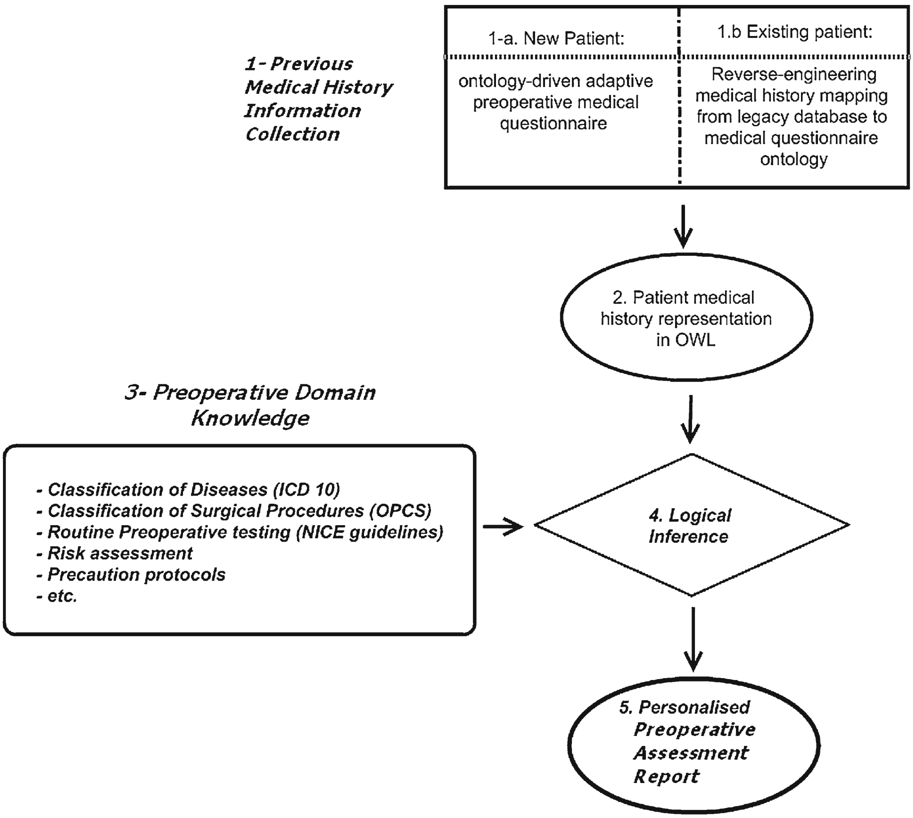

Fig. 1 Overview of knowledge-based preoperative decision support system

"heart condition" but may not be able to recall the exact name or the type of medication. While this unfortunately places some limitations on the accuracy and reliability of the patient's medical history, this is a consequence of the preoperative process itself rather then a design flaw of the decision support system. What the system can do, however, is highlight which information was obtained through a reliable clinical source or was obtained from the patient himself, so a health professional can decide to make further investigation on a specific piece of information if necessary or relevant. This additional demand on the workload of the health professional could be somehow alleviated by obtaining the relevant information directly from the medical record at the patient's family doctor if available.[2]

3. Because of the nature of preoperative assessment in attempting to identify relevant risks of complications, the domain knowledge is potentially limitless. However, for practical reasons, preoperative assessment has generally focused on generic risks (e.g. cardiovascular, respiratory) unless the patient or surgical procedure requires specific attention. We focused on designing a generic preoperative assessment decision support ontology, including information on classification of morbidities using the ICD-10 International Classification of Diseases, classification of surgical procedures based on OPCS

[2] This is the subject of a research fellowship funded by the the Scottish Health Executive, Chief Scientist Office.

(Office of Population Censuses and Surveys)[3] and other relevant evidence-based preoperative assessment medical knowledge such as the NHS NICE routine preoperative tests guidelines[4] The preoperative assessment ontology was developed in OWL [22] along the principles of modularity developed by Rector et al. [23,24] for coherent and efficient knowledge update and management [25].
4. The personalized information representation obtained at step 2 is combined with the general domain knowledge of step 3 in order to make relevant logical inferences on this specific patient [26].
5. A personalized patient preoperative report is compiled including: (i) suggested preoperative tests, (ii) risk assessments and (iii) suggested precaution protocols if relevant to the patient-specific medical context.

4 System implementation

4.1 System development tools

Prior to introducing semantic technology within the system, the preoperative software was only composed of the following elements: user input, clinical data storage and a rule engine. The preoperative risk assessment was then almost entirely based on the calculation of numeric scores. The introduction of semantic-based technology in the system enabled adaptive information collection, high-level semantic patient modelling and decision support based on patient classification rather than numeric rules only. This provides for a significant enhancement to the functionalities and capabilities of the system.

Design requirements discussed in Sect. 3.1 were implemented using semantic web technology, including automated reasoning tools operating on ontologies developed with the web ontology language OWL [22] and the java OWL application programming interface [27]. Protégé-OWL was used as the main ontology development tool [28] and the open-source Java Pellet reasoner [29].

4.2 Adaptive medical questionnaire

Context-sensitive adaptation is used to iteratively capture finer-grained information with each successive step, should this information be relevant according to a questionnaire ontology. The proposed method intends to replicate the investigating behaviour exhibited by clinicians when presented with items of information that may be cause for concern or require further attention. While the system has the potential to reduce the number of questions and thus save time and costs for healthy patients, the emphasis is rather on collecting *more* information *whenever* relevant, so a proper informed patient risk assessment can be performed. The method is robust, scalable and highly configurable [18,19,21].

4.3 Medical domain knowledge of preoperative assessment

As previously suggested, due to the nature of preoperative assessment, the clinical domain knowledge relevant for assessment is potentially limitless. Some of the important knowledge resources introduced in the system included:

3 http://www.connectingforhealth.nhs.uk/systemsandservices/data/clinicalcoding.

4 National Health Service, National Institute for Clinical Excellence. http://www.nice.org.uk/Guidance/CG3.

- Access to a knowledge base of approximately 1700 OPCS classification of surgical procedures. OPCS is the official classification of surgical procedures used by the NHS and is among other things used by hospital trusts to get reimbursed by the NHS for the procedures they carry out in the hospitals throughout the year (i.e. through the payment by results, PbR scheme by which funds are allocated according to levels of activity within the trusts). This feature is therefore of critical importance for integration of the application within hospital administrative information management systems. In addition, the OPCS knowledge base include unique OPCS code identifiers, detailed English clinical descriptions of surgical procedures, classification according to 16 major anatomical categories of procedures (e.g. vascular, thorax, abdomen, brain, etc.) and approximately 150 subcategories, allowing for fine grain classification of procedures. The repository also provides an overall surgery risk from grade 1 (minor) to grade 4 (major+) for each procedures.
- Access to the International Classification of Diseases, ICD-10 codes. This is a major feature in the application ability to classify elements of patient medical history into defined categories of morbidities (e.g. cardiovascular, respiratory, renal diseases, unusual symptoms, etc.)
- Both of these previous features are critical to the integration of national and international preoperative guidelines. One of these integrated within the application is the National Institute for Clinical Excellence (NICE) guidelines that are used to determine which, if any, investigations should be carried out on a given patient based on their clinical profile. The guidelines are complex and are often not used in practice because healthcare professionals have neither the time nor the knowledge to apply them (see Sect. 4.5).

4.4 Mechanism of decision support

In the system, decision support is usually provided in a 2-step process. The first step typically calculates risk scores using numerical formulas such as the Goldman and Detsky cardiac risk index [30], the physiological and operative severity score for the enumeration of mortality and morbidity (POSSUM) [31] or derives risk grades (e.g. ASA physical status classification grades).[5] The system does not use the decision support ontology at this stage but merely computes numeric values using an open-source Java-based rule engine (JBoss Rules[6].) Once the risk grades and categories have been derived from the first risk calculation step, the system then performs decision support using the open-source java-based Pellet reasoner to reason on the decision support ontology given a patient OWL medical history profile. Concrete examples of reasoning with the decision support ontology can be found in [25,26].

4.5 Recommendation of routine preoperative tests

The purpose of the NICE guidelines recommendations for preoperative investigations is both to avoid patients undergoing unnecessary investigations, which can be detrimental to their health, as well as more efficiently managing limited resources in the public health services. The implementation of the NICE guidelines in the decision support system is both: (i) a pragmatic and useful functionality provided to health professionals and (ii) a good example of how the use of a clinical ontology and reasoner can provide functionalities beyond the capabilities of a traditional rule engine. Regarding the first point, the table in Fig. 2 illustrates the format of the NICE guidelines recommendation for preoperative investigations. We here describe the guidelines in more details:

5 (American Society of Anaesthesiologists) ranging from ASA I (healthy patient) to ASA V (moribund).

6 http://www.jboss.com/products/rules.

Grade 1 Surgery - Adults with ASA 2 with comorbidity from Renal Disease

Test	age in years 16 to 40	40 to 60	60 to 80	over 80
Chest X-ray	NO	NO	NO	
ECG	NO			YES
Full Blood Count				
Haemostasis	NO	NO	NO	NO
Renal Function	YES	YES	YES	YES
Random Glucose	NO	NO	NO	NO
Urine Analysis				
Blood gases	NO	NO	NO	NO
Lung function	NO	NO	NO	NO

Fig. 2 Adapted from the NICE preoperative guidelines: investigations are recommended based on: patient's (i) age, (ii) ASA, (iii) comorbidities, (iv) type of surgical procedure and (v) risk grade of surgical procedure. There are 3 types of result for each test: "test recommended", "test not recommended" and "consider test"

Type of investigations: the guidelines include 9 potential investigations: chest X-ray, ECG (electrocardiogram), full blood count, haemostasis, renal function, random glucose, urine analysis, blood gases and lung function.

Type of recommendations: there are currently 3 types of recommendations for each test: "test recommended", "test not recommended" and "consider test".

Factors influencing recommendations: There are 5 factors taken into consideration in order to find the relevant recommendations: the (i) age of the patient, (ii) his ASA grade, (iii) the type of comorbidities the patient has (e.g. respiratory, cardiovascular, renal) (iv) the type of surgery (e.g. cardiovascular surgery, neurosurgery, etc.) (v) the risk grade of the surgery (from 1 to 4).

Number of cases in the guidelines: the guidelines are summarized for preoperative health assessors into 36 tables such as the one illustrated in Fig. 2. There are different tables for different combinations of the 5 factors previously described, including different tables for children under 16 years of age and adults over 16 years of age. In total, there are at least 1242 different possible cases.

Perhaps not surprisingly, we found that in practice, preoperative health assessors faced considerable difficulties in using the guidelines. The important number of factors to take into consideration in order to find the correct table and then the specific case within this table combined with the significant number of tables meant that too much time was being spent by preoperative health assessors trying to refer to the correct case. In addition, the preoperative health assessors would need to be able to categorize: (i) the type of comorbidities, (ii) their severity (e.g. for determining the patient's ASA grade), (iii) the type of surgical procedures and (iv) their surgical risk grades: all of these steps being necessary before being able to refer to the correct table. All of these tasks are obviously highly knowledge intensive as well as being intellectually demanding. In addition, preoperative health assessors typically see dozens of different patients a day, each with a wide variety of health conditions and scheduled for various types of surgical procedures. In practice, the consequences are that, if in doubt, preoperative investigations would probably be requested regardless of the guidelines (i.e. *better safe than sorry*) , thus defeating the purpose of the guidelines in efficiently managing the allocation of preoperative investigations within care delivery.

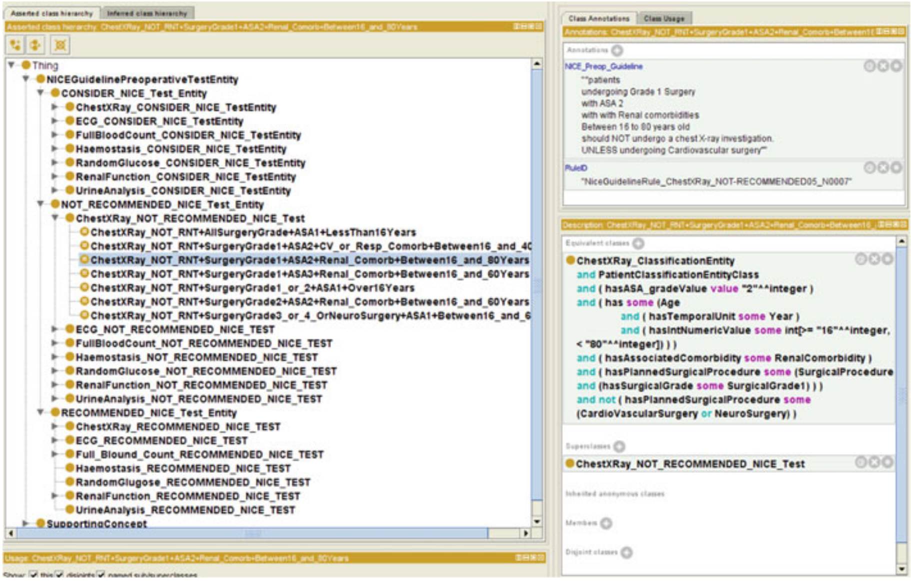

Fig. 3 The NICE guidelines as OWL rules as viewed through the Protégé-OWL user interface

We combined the use of an ontology and reasoner in the preoperative decision support system in order to automatically make recommendations regarding the suitability of tests based on the NICE guidelines. The first step consisted of transforming the NICE tables into rules. This enabled to considerably reduce overlap and redundant information in the current format of the guidelines. The 1242 different possible cases currently covered by the NICE guidelines were reduced to around a hundred rules [26]. The main advantage of modelling the preoperative investigation guidelines as OWL axioms is that the preoperative decision support system can now (i) use third party clinical taxonomies in order to allocate a surgical risk grade to a specific surgical procedure (i.e. OPCS) and (ii) use a third party clinical taxonomy to infer patient comorbidities (i.e. ICD-10) as described in Sect. 4.3. Thus, using the OWL patient medical history profile generated at the step 2 in Fig. 1, we can now automatically infer which investigations a patient should have based on his specific medical history (Fig. 3).

4.6 Example of preoperative tests recommendations

Figure 4 provides an example of preoperative test recommendation based on reasoning on the decision support ontology. Mark is a 67-year old patient, with arrhythmia, his ASA status has been estimated to be 3 and he is to undergo an open excision of lesion of duodenum. Reasoning on the recommended tests decision support ontology returns that a chest X-ray, ECG test, full blood count and a renal function tests are all recommended, a haemostasis test may be considered and a lung function test is not recommended. The recommendations are made by the system based on the following reasons:

chest X-ray: patient is over 60 and of ASA 3, in addition he has arrhythmia that is classified in the decision support ontology as a cardiovascular comorbidity, and he is to undergo an open excision of lesion of duodenum, a surgical procedure of grade 4 in the ontology.

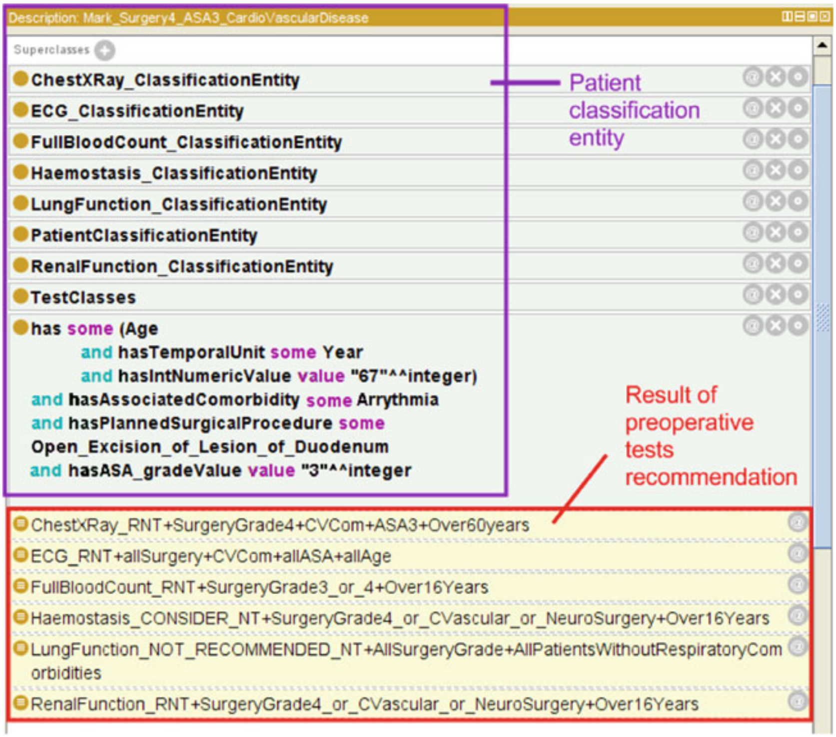

Fig. 4 Example of preoperative test recommendation based on reasoning on the decision support ontology

All this criteria mean that this patient falls within one of 2 categories of patients that are recommended for a chest X-ray investigation.

ECG: test recommended as the patient has a cardiovascular comorbidity, so he should undergo an ECG test regardless of all other factors.

Full blood count: test recommended as the patient is over 16 years of age and is undergoing either grade 3 or 4 surgery.

Renal function: test recommended as patient is over 16 and undergoing grade 4 surgery.

Haemostasis: test may be considered as patient is over 16 and undergoing grade 4 surgery.

Lung function: this test is not recommended as the patient does not have any respiratory comorbidities.

4.7 Dealing with multiple morbidities

A significant development in current world health trends is the substantial increase in the prevalence of chronic diseases and multiple morbidities within the general population, both in developed and developing countries [32]. We currently provide limited support for dealing with multiple comorbidities while processing recommendations for routine preoperative tests based on the NICE guidelines. The guidelines do not explicitly deal with the issue of multiple comorbidities, and this is an other area where the decision support tool can provide additional functionalities.

Duplication of test recommendations: In the case of a patient with multiple comorbidities, it is possible that a test may be recommended for multiple reasons. As an example, a patient of ASA 2, over 60 years of age, undergoing grade 2 surgery could be recommended an ECG test twice if he has renal comorbidities and cardiovascular comorbidities. In this case, the system can issue a *strong* recommendation alongside relevant explanation.

Conflicting test recommendations: the guidelines are not mutually exclusive and especially not in the case of multiple comorbidities. It is possible for example for a patient of ASA 2, less than 40 years of age, undergoing grade 2 surgery to be recommended an ECG test if he has cardiovascular comorbidities, but not if he has respiratory comorbidities. The contradiction is only apparent: what is not necessary for a patient with *only* respiratory comorbidities obviously becomes necessary if the patient *also* has cardiovascular comorbidities. Thus, one instance of a "recommended test" within a batch of test results leads to a positive test recommendation regardless of all other test recommendations. According to the same principle, if the system returns instances of "consider test" along "test not recommended" instances, then the system issues a "consider test" recommendation. Finally, the system issues a "test not recommended" advice only if all instances returned are negative for this specific test.

We are hoping to introduce more sophisticated support for dealing with multiple conditions, as clinical models of complex morbidities are being developed and guidelines become routinely available within the health services [33–35].

5 Conclusion and future work

We have presented our work to date on the design and implementation of a knowledge-based preoperative assessment support system. We have discussed how preoperative assessment is a generic clinical screening process, intended to identify early on in a patient journey potential risks of complications during or after surgery. By its very nature, the clinical knowledge relevant to preoperative assessment is potentially limitless. We have proposed some solutions to efficiently harness and manage preoperative assessment clinical knowledge. The system was developed using semantic web technology including modular ontologies developed in OWL, the OWL API and an automated logic reasoner. This design has provided substantial improvements on earlier versions of the systems, including the ability to tailor patient information collection according to individual medical context, the ability to efficiently manage a vast repository of preoperative assessment domain knowledge, including classification of surgical procedures and morbidities, and guidelines for routine preoperative tests.

Acknowledgments Dr. Bouamrane is a Scottish Executive Health Department Chief Scientist Office (CSO) http://www.cso.scot.nhs.uk postdoctoral fellow in health informatics and health services research working on the development of information systems to facilitate the integration of preoperative assessment across primary and secondary care in Scotland.

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Alan Rector is Professor of Medical Informatics in the School of Computer Science at the University of Manchester. He received his BA in Philosophy and Mathematics from Pomona College, his medical training at the universities of Chicago and Minnesota where he obtained his MD, and his Ph.D. in Medical Informatics from the University of Manchester. Over the past 25 years, he has led a series of projects on clinical decision support, medical records, and medical terminology including the ground breaking *PEN & PAD* project on intelligent medical records sponsored jointly by the UK Medical Research Council and Department of Health. During the 1990s, his work focused on medical terminology and ontologies. He led the EU-sponsored *GALEN programme* (www.opengalen.org) and the Department of Health sponsored UK Drug Ontology Project. He currently leads two industrial collaborations using OWL to enhance clinical systems: by using knowledge-driven clinical systems and other specialized information gathering tasks.

Martin Hurrell is Managing Director of Informatics CIS. He has a Ph.D. on computer analysis of EEG. He carried out research for a winning entry in the National SMART award competition. He was appointed CEO of Dräger Informatics and has served as Head of Strategic Planning and Information Technologies. He works as a technology consultant, advising on policies for technology in the health services. He is the technical Director of the International *Organisation for the development of Terminology in Anaesthesia, (IOTA)* and co-chair of the international HL7 Work Group for the Generation of Anaesthesia Standards. He is also a consultant to the American College of Surgeons project: *"Plan for Extracting Intra-operative Anaesthesia Data to the ACS NSQIP Database"*.