Semantic enrichment of clinical models towards semantic interoperability. The heart failure summary use case

Catalina Martínez-Costa1, Ronald Cornet2, Daniel Karlsson3, Stefan Schulz1, Dipak Kalra4

ABSTRACT

Objective To improve semantic interoperability of electronic health records (EHRs) by ontology-based mediation across syntactically heterogeneous representations of the same or similar clinical information.

Materials and Methods Our approach is based on a semantic layer that consists of: (1) a set of ontologies supported by (2) a set of semantic patterns. The first aspect of the semantic layer helps standardize the clinical information modeling task and the second shields modelers from the complexity of ontology modeling. We applied this approach to heterogeneous representations of an excerpt of a heart failure summary.

Results Using a set of finite top-level patterns to derive semantic patterns, we demonstrate that those patterns, or compositions thereof, can be used to represent information from clinical models. Homogeneous querying of the same or similar information, when represented according to heterogeneous clinical models, is feasible.

Discussion Our approach focuses on the meaning embedded in EHRs, regardless of their structure. This complex task requires a clear ontological commitment (ie, agreement to consistently use the shared vocabulary within some context), together with formalization rules. These requirements are supported by semantic patterns. Other potential uses of this approach, such as clinical models validation, require further investigation.

Conclusion We show how an ontology-based representation of a clinical summary, guided by semantic patterns, allows homogeneous querying of heterogeneous information structures. Whether there are a finite number of top-level patterns is an open question.

Key words: Electronic health record, terminology, SNOMED CT reference terminology, ontology, semantics, knowledge representation

OBJECTIVE

Semantic interoperability of clinical information has been put on many organizations’ and initiatives’ agendas. Variegated requirements for data capture and storage have motivated the development of standards and specifications for terminologies, ontologies, and clinical models. Nevertheless, the semantic interoperability problem persists.

The European SemanticHealthNet network follows the recommendations of its predecessor project, SemanticHealth, in seeking to more closely integrate information models, as used in electronic health records (EHRs), as well as terminologies and ontologies, to improve semantic interoperability. The European SemanticHealthNet network pursues this goal by dissecting heterogeneous representations of clinical information based on formal-ontological principles. Thus, a shared model of meaning enables precise annotations of what each information item in a clinical model signifies, using the Semantic Web language OWL description logic (DL). Complicated language constructs are addressed by using semantic patterns as intermediate representations.

We have chosen to focus on chronic heart failure and cardiovascular prevention as use cases. In this article, we exemplify the project’s proposed approach by focusing on the Heart Failure Summary, a structured clinical model, driven by clinicians’ requirements within SemanticHealthNet, that summarizes basic aspects of heart failure diagnosis and care in order to optimize disease management.

BACKGROUND AND SIGNIFICANCE

Semantic interoperability of EHR systems requires several layers of representational artifacts to clearly share roles. These layers are: (1) generic EHR information models; (2) clinical data structure definitions, viz. clinical models; (3) top-level ontologies; (4) domain ontologies; and (5) terminologies. Whereas the
latter three have been referred to as *models of meaning*, the former two have been referred to as *models of use*.\textsuperscript{5}

Generic EHR information models provide standardized information structures, relationships, and constraints to represent EHR data. Examples are EN ISO 13606-1,\textsuperscript{6} openEHR Reference Model,\textsuperscript{7} or HL7 Reference Information Model.\textsuperscript{8} The meaning they convey relies on the intuitive and common-sense understanding of natural language labels and descriptions, rather than a priori referencing of any ontological foundation. Eg, For instance, openEHR distinguishes between information structures for representing observation and evaluation results and instructions, while EN ISO 13606 provides a general “entry” information structure for the three cases. The meaning of terms such as “evaluation,” “observation,” “entry” are only informally elucidated in the documentation. The openEHR information model is partially ontology-based,\textsuperscript{9} but it is not rooted in any upper-level ontology and, thus, lacks a clear ontological commitment.\textsuperscript{10}

Clinical models like EN ISO 13606/openEHR archetypes,\textsuperscript{11} HL7 CDA documents,\textsuperscript{12} or Clinical Element Models,\textsuperscript{13} constrain information model structures for serving particular data capture and communication use cases. As an example, a blood pressure model constrains information structure to only record information such as systolic, diastolic, and mean blood pressure measurement results, the patient’s position, the measuring device, etc. Additionally, templates like those proposed by HL7\textsuperscript{14} or openEHR\textsuperscript{15} allow for using a set of clinical models together, constrained for addressing one or more particular documentation scenarios.

Ontologies formally describe properties and relations of types of entities. Domain-independent categories, relations, and axioms are typically provided by *top-level ontologies*,\textsuperscript{10} whereas the types of information that make up a domain are represented by *domain ontologies*. The former comprises categories like *Process*, *Material entity*, *Quality*, etc., whereas a clinical domain ontology would contain classes for *Diabetes mellitus type 1*, *Left index finger*, or *Diclofenac*, ideally covering all the terms used in clinical documentation and reporting. The terms are organized by clinical terminologies. Ontologies have, at least, a minimal terminology component, consisting of a label or preferred term to make them intelligible to a human reader. SNOMED CT,\textsuperscript{16} in addition, provides term variants and (quasi-)synonyms as possible values for data entry.

So far, there has been only partial and rather tacit consensus about the role each of the above artifacts should play and how they interface. Whereas terminology and ontology aspects are mostly covered by the same artifact (by linking terms to ontology classes), the division between ontologies and information models ideally follows the classical distinction between ontology\textsuperscript{17} (what exists) and epistemology (what is known).\textsuperscript{18} In practice, this line is often crossed both by ontologies (where they represent information entities, such as in the SNOMED CT context model) and by clinical models (where they carry their own ontology without reference to external standards).

As an example of overlapping, the SNOMED CT concept *History of vertigo* is described by following the SNOMED CT compositional syntax\textsuperscript{19}:

\begin{verbatim}
definition
  OBSERVATION[at0000] matches|-- Story/History
  data matches {
    HISTORY[at0001] matches|-- Event Series
    events cardinality matches {1..*; unordered} matches {
      EVENT[at0002] occurrences matches {0..1} matches|-- Any event
      data matches {
        ITEM_TREE[at0003] matches|-- Tree
        items cardinality matches {1..*; unordered} matches {
          CLUSTER[at0000]|-- Symptom
          items matches {
            ELEMENT [at0001] matches|-- Issue name
            value matches {
              DV_TEXT matches {*}
            }
          }
          ...
        }
      }
    }
  }
}
\end{verbatim}

This syntax does not just represent the clinical type *Vertigo*, but also epistemic (“*Known present*”) and temporal aspects (“*Past*”). *Vertigo*, itself, is signified by the code 399153001, but could also have been represented by a clinical model. \textbf{Figure 1}
On the contribution. That would be more than just free or coded text (DV(TEXT).

One could argue that ontologies should not cross this boundary, as the rules of TermInfo state. But, even in this case, the same piece of clinical information could be heterogeneously shaped by using different EHR information model structures. Within a diagnosis model, the disease and its location could be represented by using a pre-coordinated SNOMED CT concept (eg, neoplasm of lung) as a signifier; or alternatively, by using signifiers of disease (neoplasm) and location (lung) separately. Semantic interoperability requires the means to detect that both representations are equivalent, or iso-semantic (ie, carrying the same meaning, despite being represented heterogeneously).

To address this problem, the Clinical Information Modeling Initiative (CIMI) proposes a set of modeling patterns, defined as clinical models, intended as guides for the creation of new patterns. Each is associated with a set of iso-semantic models, from which one is selected as the preferred one, and mappings are established across information model structures. CIMI- or HL7-based models that implement the TermInfo specification might work well in isolation, but semantic interoperability issues arise when these models interact with others that are not necessarily compatible. In addition, anticipating all possible iso-semantic representations would lead to an explosion of models.

MATERIALS AND METHODS

Overview

Convinced that multiple EHR standards, terminologies, and ontologies as well as a large number of legacy information models, will co-exist, we created an approach that builds a semantic layer over them, acting as a proxy for applications that aim to access homogeneous content from heterogeneous repositories. This semantic layer consists of two sublayers that include a set of semantic patterns and an ontological framework.

The ontological framework’s objective is two-fold. Firstly, it provides a formal foundation that helps standardize information modeling tasks. Agreement at this level is essential to give interoperable meaning to heterogeneous EHR modeling styles. Secondly, the formal representation of clinical information conforming to an ontological framework adds value through DL style reasoning and advanced querying.

Semantic patterns, as close-to-user representations that hide the complexity of the ontology language, prevent modelers from the error-prone creation and maintenance of OWL expressions.

In order to access homogeneous clinical information from heterogeneous clinical models, the following steps must be carried out: (i) identify semantic patterns to encode the information captured by clinical models and define their correspondences; (ii) instantiate the patterns with data; and (iii) create sample queries of the data.

Ontological framework

The ontological framework consists of three OWL DL ontologies: (i) SNOMED CT, as the domain ontology; (ii) BioTopLite2 (BTL2), as the top-level ontology; and (iii) an information entity ontology, which represents recurring elements of information addressed by EHR information models.

BTL2 (prefix “btl”) is a reduced version of BioTop, a top-level domain ontology tailored for the biomedical domain. It provides upper-level types for both domain and information entities, as well as constraints on either, using a set of canonical relations partly derived from the OBO Relation Ontology. Axioms express disjointedness between classes; constrain the domains and ranges of relations; and also define relation chains as well as existential and value restrictions at the class definition level. Thus, ontology creation under BTL2 heavily constrains the freedom of the ontology engineer, which is intended, as it results in higher predictability of the ontologies produced.

SNOMED CT (prefix “sct”) acts as a common reference point for representing the clinical content by modules based on its OWL version. Its content is largely harmonized with basic top-level classes and relations of BTL2. SNOMED CT’s ontological commitment has been subject to intense debate in recent years, and its consolidation is ongoing. Based on, we interpret SNOMED CT “Finding/Disorder” concepts as clinical situations. In addition, we have reinterpreted the SNOMED CT context model in order to better distinguish clinical entities from information ones.

Finally, the EHR information entity ontology (prefix “shn”) represents pieces of clinical information as documented in the EHR. They are outcomes of actions like observations, investigations, or assessments. All these outcomes refer to clinical entities and are further described by attributes of epistemic and contextual aspects like clinical history or confirmed/suspected diagnosis. All classes of this ontology are represented as subclasses of the BTL2 top-level class bt:InformationObject. Information entities refer to clinical entities by means of the relations shn:isAboutSituation and shn:isAboutQuality, both defined as a specialization of the relation bt:represents. As a subclass of bt:InformationObject, we used the class shn:InformationItem to represent information entities that refer to a clinical situation and the class shn:ObservationResult to refer to directly or indirectly observed qualities, such as skin color or heart rate, to which a value is assigned.

Additionally, we created the class shn:InformationAttribute to represent parts of information entities that express epistemic status, like Suspected or Probable.

Semantic patterns

Ontology content patterns are reusable solutions to recurring modeling problems. They have fixed and variable parts and are explicitly ontology-based, unlike databases schemas or UML models. In our context, named Semantic Patterns, they guide and standardize the meaning of the content of clinical models and also bridge the following approaches developed by distinct communities: EHR modeling, Semantic Web, and formal ontology.
Figure 2 depicts the semantic representation of an openEHR archetype for symptom information. The archetype consists of a set of nodes or data elements, which are constrained by value sets. White rectangles represent ontology classes, which are connected by directed arcs that represent quantified object properties. Such a representation is already a semantic pattern, with ontology classes as variable parts (since they can be specialized); and the classes to use and their relationships as fixed parts.

To obtain this representation, each node (eg, CLUSTER, ELEMENT) of an archetype needs to be attached to the ontology according to two aspects: (a) the information model class it corresponds to and (b) the clinical entity it represents. The latter may require further subclassing, ie, classifying an entity as a quality (eg, skin color), clinical situation (eg, cancer), etc.

In Figure 2, the archetype nodes (gray boxes) are placed next to their corresponding ontology top-level classes. At the core of the diagram is shn:SymptomRecord, the class of all information entities that represent some symptom, ie, a clinical entity in the shn:ClinicalSituation class. For the rest of the archetype nodes, the same rationale is used. Some ontology classes are connected to the shn:SymptomRecord class and others to the shn:ClinicalSituation class, depending on whether the classes provide some epistemic information about the symptom or whether they further describe it. For instance, the archetype node labeled “Progression” is described as “The progress of the symptom relative to the past” and may take a value out of the set “Improving, Decreasing, Stable, Increasing, Worsening or Resolved.” Since it reflects the perception of a symptom, it is epistemic information (shn:Status) and, therefore, connected with shn:SymptomRecord. Their internal axioms (here <shn:hasInformationAttribute some>) control how both classes are related within the ontology. This assures the pattern’s consistency, which can be ascertained by DL reasoning.

Our hypothesis is that a limited set of generic patterns simplifies the modeling task. Patterns such as the one for the symptom archetype could be created by specializing and composing a set of top-level patterns, following principles that are similar to the object-oriented paradigm. Figure 3 depicts the two top-level patterns from which the symptom pattern can be derived. Multiple archetype nodes correspond to one top-level ontology class. Thus, ontology classes and their corresponding relationships will be specialized in order to obtain the representation shown in Figure 2.

Use case description
For this study, we used an excerpt of the Heart Failure Summary, developed within SemanticHealthNet and represented as an openEHR template. We demonstrate that information represented by clinical models can be expressed by semantic patterns, or compositions thereof, using a set of finite top-level patterns from which the semantic patterns are derived. Furthermore, we show how heterogeneous
representations of the same or similar clinical information can be queried homogeneously.

We implemented two test desktop applications for heart failure data recording (Applications A and B), based on different clinical models that embed similar information into heterogeneous structures at different levels of detail. Each application consists of a set of constrained data elements bound to SNOMED CT terms. A tool developed within IHTSDO, which implements the SNOMED CT query language, defines reference sets from the terminology. Figure 4 shows the entry forms that record symptom information.

Application A records the presence or absence of predefined symptoms by using a checklist, together with the heart failure stage, created from a SNOMED CT subclass of the New York Heart Classification finding class. Application B provides a different set of symptoms whose presence or absence can be indicated with the SNOMED CT terms Known present and Known absent, respectively. Additionally, Application B allows a user to record the severity of a symptom by selecting a severity value. The recording of the New York Heart Classification finding class is done in the same way as in Application A.

Comparing both applications, structural heterogeneities exist in the representation of the presence/absence of symptoms (check list vs. known present/known absent terms). Figure 5 depicts an excerpt of the applications’ representation as ADL openEHR archetypes, where the symptoms’ presence or absence is represented as an OpenEHR CLUSTER containing two ELEMENTs, one for the symptom itself (ELEMENT[at0001]) and one for representing its presence (ELEMENT[at0002]). The level of detail the two applications require also differs. For instance, Application A requires the additional recording of each symptoms’ severity (ELEMENT[at0005]).

RESULTS

Identification of semantic patterns and definition of correspondences

The nodes from the archetypes shown in Figure 5 map to semantic patterns. Since they record symptom information, we applied the pattern from Figure 2 in order to represent the symptom itself, its presence or absence, and its severity, if indicated. Figure 6 shows the correspondences between the nodes of one of the archetypes and an excerpt of the symptom pattern.

Ontology classes (represented by rectangles) represent the pattern’s variable parts. The archetype node values are introduced as subclasses (represented as dashed rectangles), corresponding to SNOMED CT classes. Table 1 shows the OWL DL rendering of the pattern. Negation is expressed by an additional OWL DL representation, which describes the absence of a symptom as a kind of symptom record about a patient’s situation while not including any symptom of that type. As described in “Methods,” this semantic pattern could have been obtained as a specialization of the top-level pattern shown in Figure 3. Both – the symptom severity and its presence or absence – are subclasses of the information attribute class.
used to represent epistemic and contextual information (shn:InformationAttribute).

Instantiation of semantic patterns with patient data
When archetypes (already related to semantic patterns) are instantiated with patient data, a set of OWL DL-conforming pattern instances are generated. Table 2 shows the instances generated for the data recorded for two fictitious patients, Patients A and B, by Applications A and B, respectively. Only instances of subclasses of shn:InformationItem, btl:Process, and shn:Patient are created; their type is a logical expression conforming to the OWL DL symptom pattern representation (cf, Table 1). The pattern variables have been replaced by SNOMED CT terms, provided as patient data, and placed under the corresponding ontology classes (eg, sct:ChestPain, as a subclass of shn:ClinicalSituation, sct:Mild, as a subclass of shn:Severity).

Homogeneous querying of pattern-based data instances
To query the patient data, we have used SPARQL, extended for the OWL Direct Semantics entailment regime (SPARQL-OWL), which provides more expressive semantics than SPARQL’s standard simple entailment. This extension, implemented by the OWL-BGP API, is independent of the DL reasoner we used. For the DL reasoner, we used FaCT++ and TrOWL. A systematic evaluation of which reasoners perform better was out of our study’s scope. Table 3 depicts the two SPARQL queries used to retrieve symptom-related information for Patients A and B. The queries follow the symptom pattern, and using the reasoner allows for their formulation at different granularity levels, compared to the level provided when the data was entered.

Query1 retrieves instances of information about Patients A and B, although the patient data entered is not the same (the
SNOMED CT term breathlessness on exertion is a subclass of breathlessness).

Query 2 retrieves only data from Patient B. Although the query asks for patients with breathlessness, it also explicitly asks for those who do not have breathlessness at rest, and this information has not been stated for Patient A (however, the absence of information does not mean that the symptom is excluded).

Both queries use DL reasoning. The execution times, using an Intel Core i5-3470 3.20 GHz, 8GB, are: TrOWL Q1:1.183s, Q2:1.706s; FACT++ Q1:1.316s; and Q2:3.053s.

**DISCUSSION**

We have used a Heart Failure Summary to demonstrate how semantic patterns can be applied to enable querying of heterogeneous representations of patient information. OWL DL representations for use in the EHR have been proposed by several authors. However, they are dependent on particular modeling approaches and, therefore, are not interoperable. In contrast to our approach, most others only represent structural aspects of the clinical models and do not address the embedded meaning of these aspects (eg, "ELEMENT structure with allowed value CODED_TEXT," instead of "Diagnostic information about a disease"). We hypothesize that, without any ontological commitment and formalization, the creation of ontologies adds just another complexity level to the EHR and is useless for interoperability.

A. Rector et al. distinguish "models of meaning" (describing our understanding of the world) from "models of use" (describing how data are displayed or captured). The latter models are designed for specific use cases, while the former are largely stable and context-independent.

Semantic patterns provide certain structure but are not designed to allow several data-capture possibilities at the point of care (eg, drop-down menus vs. checklists). However, we have to admit plurality into these systems, because universal agreement on how to capture information is not realistic.

Semantic interoperability requires EHR systems to share their "models of meaning." To this end, we have proposed semantic patterns as a bridge between heterogeneous EHR representations and a shared model of meaning. They also have the potential to ensure that more specific models, such as that

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**Figure 5:** (Left) Excerpt of an ADL OpenEHR archetype that records the presence/absence of symptoms as a checklist, by using a Boolean data type, “True” meaning “symptom present” and “False” meaning “symptom absent” (Application A). (Right) Excerpt of an ADL OpenEHR archetype that records the presence/absence of symptoms by using a coded text data type that represents the SNOMED CT terms Known present and Known absent, and also allows for recording a symptom’s severity (Application B).
proposed by CIMI, are semantically valid derivations from higher level patterns. It will be necessary to further investigate the extent to which semantic interoperability can be achieved at the pattern level by using other representation language, such as the Resource Description Framework (RDF), with limited or no DL reasoning at all. It is well known that DL reasoning does not occur with zero cost, and, therefore, it may increase the query execution time beyond acceptable limits. This is the case in the OWL-BGP implementation. Optimization strategies are subject of current research, and some of them are implemented by the OWL-BGP API; however, the execution time may still be unacceptable for real-world implementations.

Some of the SNOMED CT concepts we have used in this article have been re-interpreted to clarify, rather than change, their meaning. Issues could arise if the re-interpreted meaning differs from the one intended when the code was originally used. Variability in coding is an unavoidable problem, but clarification in naming (in)formal definitions will decrease intercoder variability. Results from the SemanticHealthNet project have also been fed back to the SNOMED CT curators.
CONCLUSION

The semantic infrastructure proposed here addresses the complexity of the medical domain, as well as its heterogeneous data capture and re-use needs, by proposing a semantic layer over existing EHR representations, which will be able to provide homogeneous access to heterogeneous data sets. They are heterogeneous not only because they use different representational languages, modeling approaches, etc., but also because they differ in context and granularity.

A set of DLs ontologies constitute the core of the proposed semantic layer. All of them adhere to formal ontology principles and exhibit reasoning capabilities. A top-level ontology enforces crisp boundaries between different entity types, which keeps the modeling process as standardized as possible, yet also balances what is ontologically correct and what is useful in practice.

One severe obstacle may be the requirement for those who have to model clinical information according to the proposed ontologies to possess deep ontology engineering skills. This has been addressed by simplifying semantic patterns, which help standardize the ontology-based modeling of clinical information through specialization and composition mechanisms. By looking at the existing content patterns available at the ontology pattern community site, we did not find specific patterns for the modeling of clinical information. Instead, patterns, such as the agent-role or action ones, could be reused. Whether there are a finite number of top-level patterns from which the others will specialize is still an open question. At this stage, we can confirm that the representation of the Heart Failure Summary provided a high degree of information heterogeneity and that a reduced number of top-level patterns were derived from that representation.

So far, we have based patterns on an underlying OWL DL formalism. Their representation in RDF is the subject of our current work. The former pattern allows for logical reasoning and, therefore, a more advanced exploitation of information (although, performance issues might limit their implementation in real systems). In this case, RDF representations might be more appropriate, though they are less

<table>
<thead>
<tr>
<th>Table 2: OWL DL pattern instantiation with symptom-related data captured by Applications A and B, for Patients A and B, respectively</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>PATIENT A - Application A: Breathlessness and chest pain symptoms</strong></td>
</tr>
<tr>
<td><strong>Individual:</strong> SymptomEvaluationProcess_PatientA</td>
</tr>
<tr>
<td><strong>Type:</strong> sct:EvaluationSignsAndSymptoms</td>
</tr>
<tr>
<td>and btl:hasParticipant value PatientA</td>
</tr>
<tr>
<td><strong>Individual:</strong> SymptomA_Breathlessness_Present</td>
</tr>
<tr>
<td><strong>Type:</strong> sct:Breathlessness</td>
</tr>
<tr>
<td>and btl:hasParticipant value SymptomEvaluationProcess_PatientA</td>
</tr>
<tr>
<td>and sct:isAboutSituation only sct:Breathlessness</td>
</tr>
<tr>
<td><strong>Individual:</strong> SymptomA_ChestPain_Present</td>
</tr>
<tr>
<td><strong>Type:</strong> sct:Breathlessness</td>
</tr>
<tr>
<td>and btl:hasParticipant value SymptomEvaluationProcess_PatientA</td>
</tr>
<tr>
<td>and sct:isAboutSituation only sct:ChestPain</td>
</tr>
<tr>
<td><strong>PATIENT B - Application B: Mild breathlessness on exertion but not at rest symptoms</strong></td>
</tr>
<tr>
<td><strong>Individual:</strong> SymptomEvaluationProcess_PatientB</td>
</tr>
<tr>
<td><strong>Type:</strong> sct:EvaluationSignsAndSymptoms</td>
</tr>
<tr>
<td>and btl:hasParticipant value PatientB</td>
</tr>
<tr>
<td><strong>Individual:</strong> SymptomB_BreathlessnessOnExertion_Present</td>
</tr>
<tr>
<td><strong>Type:</strong> sct:BreathlessnessOnExertion</td>
</tr>
<tr>
<td>and btl:hasParticipant value SymptomEvaluationProcess_PatientB</td>
</tr>
<tr>
<td>and sct:isAboutSituation only sct:BreathlessnessOnExertion</td>
</tr>
<tr>
<td>and sct:hasInformationAttribute some sct:Mild</td>
</tr>
<tr>
<td><strong>Individual:</strong> SymptomB_BreathlessnessAtRestAbsent</td>
</tr>
<tr>
<td><strong>Type:</strong> sct:BreathlessnessAtRest</td>
</tr>
<tr>
<td>and btl:hasParticipant value SymptomEvaluationProcess_PatientA</td>
</tr>
<tr>
<td>and sct:isAboutSituation only (sct:BreathlessnessAtRest)</td>
</tr>
<tr>
<td>Note: Other instance exemplars can be accessed here.</td>
</tr>
</tbody>
</table>

Table 3: SPARQL queries rendered using Turtle syntax

<table>
<thead>
<tr>
<th>Query 1: Information about patients with breathlessness</th>
</tr>
</thead>
</table>
| SELECT ?SymptomRecord 
  WHERE {
    ?SymptomRecord a [ 
      a owl:Class; 
      owl:intersectionOf (shn:InformationItem 
        [a owl:Restriction; 
        owl:onProperty shn:isAboutSituation; 
        owl:allValuesFrom sct:SCT_267036007] 
        [a owl:Restriction; 
        owl:onProperty btl2:isOutcomeOf; 
        owl:someValuesFrom sct:SCT_409060008] 
        )]. 
  } |

Answer: {SymptomA_Breathlessness_Present, SymptomB_BreathlessnessAtRest_Present}

<table>
<thead>
<tr>
<th>Query 2: Information about patients with breathlessness but not at rest</th>
</tr>
</thead>
</table>
| SELECT ?SymptomRecordDyspnea ?SymptomRecordNotRest 
  WHERE {
    ?SymptomRecordDyspnea a [ 
      a owl:Class; 
      owl:intersectionOf (shn:InformationItem 
        [a owl:Restriction; 
        owl:onProperty shn:isAboutSituation; 
        owl:allValuesFrom sct:SCT_267036007] 
        [a owl:Restriction; 
        owl:onProperty btl2:isOutcomeOf; 
        owl:hasValue ?EvaluationProcess]). 
    ?SymptomRecordNotRest a [ 
      a owl:Class; 
      owl:intersectionOf ( 
        [a owl:Class; 
        owl:intersectionOf (shn:InformationItem 
          [a owl:Restriction; 
          owl:onProperty shn:hasInformationObjectAttribute; 
          owl:someValuesFrom sct:SCT_410516002)] 
          [a owl:Class; 
          owl:intersectionOf (shn:InformationItem 
            [a owl:Restriction; 
            owl:onProperty shn:isAboutSituation; 
            owl:allValuesFrom [a owl:Class; 
            owl:intersectionOf (shn:ClinicalSituation 
              [a owl:Class; 
              owl:complementOf [a owl:Restriction; 
              owl:onProperty btl2:hasPart; 
              owl:someValuesFrom sct:SCT_161941007]])] 
              [a owl:Restriction; 
              owl:onProperty btl2:isOutcomeOf; 
              owl:hasValue ?EvaluationProcess])]). 
    } |

Answer: {SymptomB_BreathlessnessOnExertion_Present, SymptomB_BreathlessnessAtRestAbsent}
expressive and, therefore, more limited, in terms of information exploitation.

The use of patterns not only for interoperability purposes but also to guide the creation of clinical models and to detect semantic inconsistencies in those models is also the subject of current and future research.49

As in the case of existing EHR modeling approaches, an important feature for a successful approach is providing users with proper tools that isolate them from any technical detail. One of the biggest challenges is motivating industry partners to invest in such solutions.

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CONTRIBUTORS

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COMPETING INTERESTS

None

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