The Utilization of Artificial Intelligence for Developing Autonomous Social Robots within Health Information Systems ⋆

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Abstract
This study focuses on using AI systems, specifically conversational agents (CAs), to improve information flow during peak hours in healthcare emergency departments (EDs). We customized a Cross Industry Standard Process for Data Mining CRISP-DM approach to a CRISP-Knowledge graph (CRISP-KG) for overall design research. We use a knowledge graph approach to create an intelligent knowledge base (KBs) for CAs, which can enhance their reasoning, knowledge management, and context awareness abilities. We employ a collaborative methodology and ontology design patterns to develop a formal ontological model. Our goal is to build intelligent KBs for CAs that can interact with end-users and improve care quality in EDs, using Semantic Web Rule Language (SWRL) for inference. The KG approach can assist healthcare practitioners and patients in managing information flow more efficiently in EDs, ultimately improving care outcomes.

Keywords
Knowledge Management (KM), SWRL, Conversational Agents (CAs), CRISP-KG, ED

1. Introduction

In recent years, the inclusion of artificial intelligence (AI) applications has been developed for organizations to manage domain users' inquiries automatically and aim to develop intelligent systems that can stimulate human-like mimics with reasoning abilities [1]. The term conversational agent (CAs) or social robot is considered an intelligent program that stimulates natural language through adopting machine learning (ML) and knowledge representation and reasoning

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(KRR or KR^2), and management techniques principles [2]. The CAs applications (new kinds of information systems) in healthcare assist patients with answers to specific health-related queries and help healthcare professionals as social robots with co-working abilities [3, 4].

Nowadays, Conversational AI has become the arena and is considered one of the most active research areas. The range varies, from rule-based conversational systems, such as ELIZA [5], to the recent open domain, data-driven CAs like Apple's Siri, Google Assistant or Amazon's Alexa [1]. Few CAs in the healthcare sector cover closed domains, especially in a hospital's emergency department (ED). These systems follow multiple techniques such as pattern matching and ontologies [6] from the domain corpora and compute a response without understanding the conversation. Lack of understanding within the content, based on contextual knowledge and conversational data related to a specific scenario, these CAs have some reasoning constraints.

The CAs usually have autonomous human-machine interaction (HMI) capabilities and act as assistants at workplaces and homes [7]. Model contextual knowledge and its environmental constraints need sophisticated methods used in knowledge model-ling cycles, such as Ontologies and Knowledge Graphs (KGs) [8]. Ontology is considered a mechanism to conceptualize the domain knowledge for defining formal and explicit specifications of shared concepts and their relationships with other entities to support increased flexibility, re-usability, etc. [9]. KGs and Ontologies are regarded as the same concept and are used interchangeably. The schema for KGs can be defined as ontology, which shows the properties of a specific domain and its contextual knowledge and how they are related [10].

Knowledge representation (KR) is an essential step towards automating reasoning in developing context-aware CAs. The demand for ontology-based KRR techniques [11] is considered a powerful tool that provides sophisticated domain knowledge for processing complex social robotic tasks, making decisions, and interacting with do-main users in a real-world environment [12]. However, developing these knowledge-based social robots with inference and data-driven capabilities is a challenge.

The research study focuses on developing autonomous social robots, such as CAs, that work to reduce the time users spend seeking relevant information in hospital settings using knowledge-based intelligent CAs. This study proposed a semi-automated approach which helps to design the CAs with knowledge reasoning abilities by using Semantic Web Language Rules (SWRL[1]); a rule language for semantic artefacts, and domain knowledge including ontologies and external knowledge models to provide health-related services. It could serve as a co-worker with healthcare professionals to facilitate them and answer users' queries automatically with reasoning abilities in the emergency unit.

This study also highlights the process of context-awareness modelling, which is responsible for modelling data in a systematic way. This modelled data is processed further from high-level situation information to low-level situation information in the reasoning phase, and end-users can retrieve information through a sophisticated knowledge graph [13]. The contextual knowledge of the paediatrics emergency department (PED) can be found in (section 3.1) and a detailed case study [14].

This paper is structured with the following sections: Section 2 provides a brief overview of desktop research related to KRR or KR2 techniques, KGs for AI systems, and context-aware

[1]https://www.w3.org/Submission/SWRL/

rules. Section 3 presents the methodology; case study, customized CRISP-KG approach for the research design process, and collaborative methodology (CM) using ontology design patterns (ODPs). Section 4 presents the result and discussion. Section 5 explains the evaluation and testing results. Section 6 describes the conclusion.

2. Theoretical Background

As a branch of symbolic AI, KB systems are based on some domain of interest in which symbols surrogate real-world artefacts such as physical objects, events, relationships, etc. [15].

2.1. Knowledge Representation and Reasoning (KRR or KR^2) Techniques

The KR is a field of AI that focuses on capturing information about the real world that can be used to solve complex problems. It helps structure the domain knowledge with essential properties such as representational accuracy, inferential adequacy, inferential efficiency and acquisitional efficiency to make it more reasonable and rational with high impact. A variety of KR schemes have been discussed, such as logical representation (LR), procedural representation (PR), network representation (NR), and structured representation (SR). The KRR aims at designing AI systems that reason about a machine-interpretable representation of the domain knowledge, similar to human reasoning manipulating these symbols [16].

According to the Semantic Web (SW) technologies standards, domain knowledge appears in different forms, most notably based on semantic networks, rules, and logic [16]. The semantic network is taken as a graph where nodes represent concepts and arcs represent relations between concepts and follow a triplet structure, for instance: subject-predicate-object →(University-locatedIn-GeographicRegion)—the network expression is (Halmstad-locatedIn-Sweden)). Similarly, another form of expressing knowledge is called rules that reflect the notion of consequence in the form of IF-THEN expressing knowledge (e.g. IF the student studies in a university, THEN he is enrolled there) [17].

The KR is an essential recipe for developing AI-based applications and expert systems (ES) KBs with reasoning behaviour, especially for agents' development. The information used in KBs is derived from human experts and a collection of business rules. Initially, the knowledge is almost incomplete and uncertain, then need to make it more logical; some rules are used to associate facts with a confidence factor. It also follows schemes such as forward-chaining and backwards-chaining algorithms [18]. In the development of AI systems, various knowledge types are utilized, including structural, heuristic, meta-knowledge, factual, implicit, explicit, tacit, declarative (conceptual), and procedural knowledge. Declarative and procedural approaches are used in designing KB agents, with declarative knowledge expressed in declarative sentences and procedural knowledge encoding desired actions or behaviours [17].

2.2. Knowledge Graph for AI Systems

Ontology construction is one essential stage of KGs for AI-based System development. A knowledge graph schema can be represented by an ontology that illustrates the characteristics of a particular domain and its interconnections. Ontology is considered a creative tool essential in knowledge acquisition (KA) activities, management and its representation in various data rendering machine-readable forms [19]. Recent research on KGs gained extensive interest in academia as well as in the industry for a number of AI applications such as recommendation and fraud-detection systems [10]. Similarly, applying different business or domain rules makes it a more specialized field of AI for developing intelligent KBs systems, CAs, games, health information systems (HIS) and decision support systems (DSS), especially in the healthcare sector.

This study emphasizes knowledge reasoning using rule-based logic methods for knowledge acquisition and representation that reflects domain knowledge, especially in healthcare. We customized various ontologies related to healthcare practitioners, such as competence ontology [20], conversational ontology; Convology [21], disease ontology[2], and domain ontology related to ED context for the development of the intelligent CAs' KB. These ontologies and rule-based methods are helpful for the development of AI-based systems such as conversational agents (CAs) in the healthcare domain.

2.3. Context-Aware Rules

In most cases, the KR is a mixture of implicit and explicit knowledge available to users or machines via the inference process and formalized into different forms such as symbols, frames, semantic networks, conceptual graphs, inference rules and sub-symbolic patterns [22]. The construction of context-related rules written with the consensus of domain experts and users helps develop a variety of CAs with inference power to give the optimal answers against the query [23]. However, KR is considered a method to encode knowledge in intelligent systems KB with the help of three primary reasoning techniques: ontology-based reasoning, case-based reasoning and rule-based reasoning [24].

Rule-based reasoning, which explicitly defines and executes business rules or domain knowledge to infer new knowledge creation is more common. The context-aware rules are called semantic rules and written in semantic web rule language (SWRL), represented as entailment between antecedent (body) and consequent (head). These apply to OWL[3] ontologies enabling the reasoner to make inferences and deductions based on the present discussion of ED [13]. The SWRL supports rules consisting of an antecedent and consequent, which internally compromises positive conjunction of zero or more atoms and does not support negative atoms or disjunction [25]. The structure of the SWRL followed the IF-THEN scheme for symbolic rule formalization with logic and translated into the logical formal. This example is taken as a model to demonstrate the anatomy of rule formalization with symbolic statements [16]. SWRL schema can be seen in various formats, such as XML[4] concrete syntax and human-readable forms involving logic predicates.

Ontology-based reasoning provides general classes or object axioms associated with the domain or temporal knowledge for making more controlled information with certain constraints.

[2]https://disease-ontology.org/community/use-cases
[3]https://www.w3.org/OWL/
[4]https://www.w3.org/XML/

Ontology designing editors (e.g., protege[5], TopBraid[6] Composer etc.) are used to construct ontology or dump KBs. We followed various reasoners (e.g., Pallet[7], Ontop[8], Hermi[9], etc.) to make it more sensible and rational. We represent domain knowledge in symbolic statements and rule-based formalization.

3. Methodology

3.1. The Karolinska University Hospital Case

This study is based on a real-time case observation in the PED of Karolinska Hospital in Solna, Stockholm, Sweden. We conducted modelling workshops with multidisciplinary experts at the hospital. We followed specific steps [26] to facilitate better communication with domain users, medical professionals and experts responsible for emergency patient treatment procedures and explain ED workflows. Initially, We observed and tried to reverse engineer the whole situation of the ED. We analyzed the information flows processes related to the patient's treatment and admission procedure at the time of arrival at PED. After some assessment and establishing consensus, We traced some critical problems associated with patient-centric treatment procedures. We aimed to transform from an As-Is situation to a To-be situation in ED. From extensive desktop research, 75% of patient visits increase yearly at ED and affected patients are used to confronting unexpected experiences such as long waiting times and overcrowding issues[10] [27].

From the Hospital's perspective, a poorly functioning ED affects overall activities and workflows within the emergency unit, so it must be well organized. To get appropriate medical assistance, we need to deploy classified information systems (IS) such as Triage (e.g., decision support system (DSS)), electronic health records (EHR), and electronic medical records (EMR). The EHR focuses on the patient's overall health and sharing information with other healthcare practitioners. Similarly, the EMR contains the medical and treatment history of the patient. Here, the Triage's role is quite promising because it helps prioritize the patients for care and treatment. Unfortunately, a massive amount of patients and a long waiting queue creates a bottleneck at Triage in ED. So we need supporting technological solutions such as conversational agents (CAs) (e.g., chatbot, etc.) that help improve multiple steps in front-end Triage procedures with inconsistent practices. These also minimize the high percentage of patient handling in the waiting room during peak hours in the ED. They also help to initiate single-window operations to improve communication issues and harbour data silos within departments and treatment areas [27].

From the Patient's perspective, the long-waiting times in the ED, often accompanied by high anxiety levels, can cause the patients lose trust in health services. When EDs function poorly,

[5]https://protege.stanford.edu/
[6]https://franz.com/agraph/tbc/
[7]https://www.w3.org/2001/sw/wiki/Pellet
[8]https://www.w3.org/2001/sw/wiki/Ontop
[9]http://www.hermit-reasoner.com/
[10]https://www.usacs.com/services/case-studies/organizational-transformation-at-a-pediatric-emergency-department

this jeopardizes the health and safety of the patient and public trust in the healthcare system as a whole.

3.2. Customized CRISP-KG Approach for Research Design Process

A customized CRISP-KG approach derived from the Cross Industry Standard Process for Data Mining (CRISP-DM) approach [28] is utilized in the study. The aim was to design a research process and evaluate a novel artefact with competence questions (CQs) related to the ED context. The outcome of a CRISP-KG study should be an artefact in the form of KGs, which depicts the discussion associated with ED. This approach follows certain steps; business understanding, data understanding, data preparation, design of KGs model, KGs creation and upgradation, evaluation and deployment to ensure a systematic research design process.

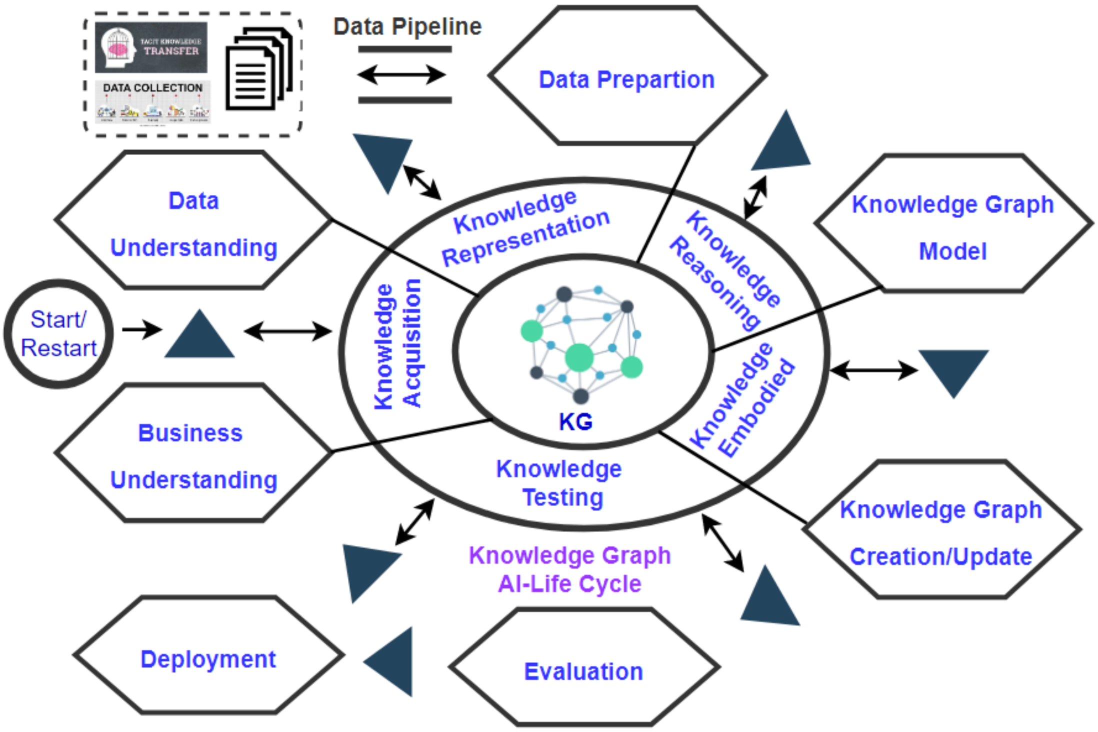


Figure 1: Customized CRISP-KG Approach for Research Design

Business and data understanding stages are interlinked with the KA layer, which is responsible for taking the data from different sources and helping transfer various data to the next level of data preparation. The execution of these steps can be seen in figure-1. The Data preparation (DP) stage takes the data and draws a lightweight database called taxonomies and then transforms it into the ontological model called the heavyweight model, which correlates with the KR layer. Similarly, the KGs model stage follows business rules, and with the help of SWRL, rules are ingested into the OWL model to make it a more rational and intelligent KB. It is also attached to the KRR layer. The KGs creation and upgradation stage involves the KE layer, which contains the business rules parsed with IE and stored in KGs. In the evaluation stage, KG is verified with CQs and attached to the knowledge testing (KT) layer to ensure the quality of the ontological model in KGs creation. The last stage is the development and delivery to developers for developing various services related to healthcare to facilitate healthcare professionals, patients, and their relatives in ED.

3.3. Collaborative Methodology (CM) for Ontology Development Using Ontology Design Pattern (ODP)

Different mature ontology development methodologies, such as Methonotology [29], and Toronto Virtual Enterprise (TOVE) [30] are available for ontology development. However, these methodologies are pretty prominent in adopting the workflow of specification, conceptualization, implementation and evaluation but need more collaboration and active involvement of the stockholders in the healthcare domain. This study followed collaborative methodology (CM) to define concrete steps for developing DO of ED related to the healthcare sector [31]. One of the exciting features of this approach is the active participation and engagement of domain experts in developing the collaborative ontological model, especially in the specification and conceptualization phase. The CM is highly dedicated towards health sciences ontologies. It follows a "meet-in-the-middle" approach where concepts are emerged both in the bottom-up approach (i.e. analyzing the domain and interviewing the domain experts regarding their data needs) and the top-down approach (i.e. analyzing and integrating existing ontologies, vocabularies and data models). These concrete steps of the CM are discussed in the following phases; specification, top-down and bottom-up conceptualization, Ingestion of ODPs [32], implementation and evaluation [31]. The following figure 2 demonstrates a systematic way of these steps for better realization.

3.3.1. Specification

This phase is associated with the scope of the study and requirements, which are a core part of the development of the semantic model (e.g., taxonomies, ontological model, etc.). The ontology modeller identifies the core information related to the specific domain along with domain experts in modelling workshops. This information presents in the semantic model using different data acquisition (DA) techniques, such as modelling techniques [33]. They also contribute their input and feedback through brainstorming, interviews and questionnaire completion.

3.3.2. Conceptualization Phase and Top-down/Bottom-Up Strategies

This phase highlights the importance of conceptual modelling and identifies different domain-related concepts, entities, and their relationships among concepts. The conceptualization phase is categorized into sub-sections which helps in the ontology model process and its development.

These sub-sections are described as identifying the core concepts which can be extracted from the CQs related to the domain knowledge, identifying related models and ontologies, analyzing them and reusing concepts and vocabularies. These sub-sections aim to find the most suitable semantic models and ontologies that can be reused in the target DO that should be

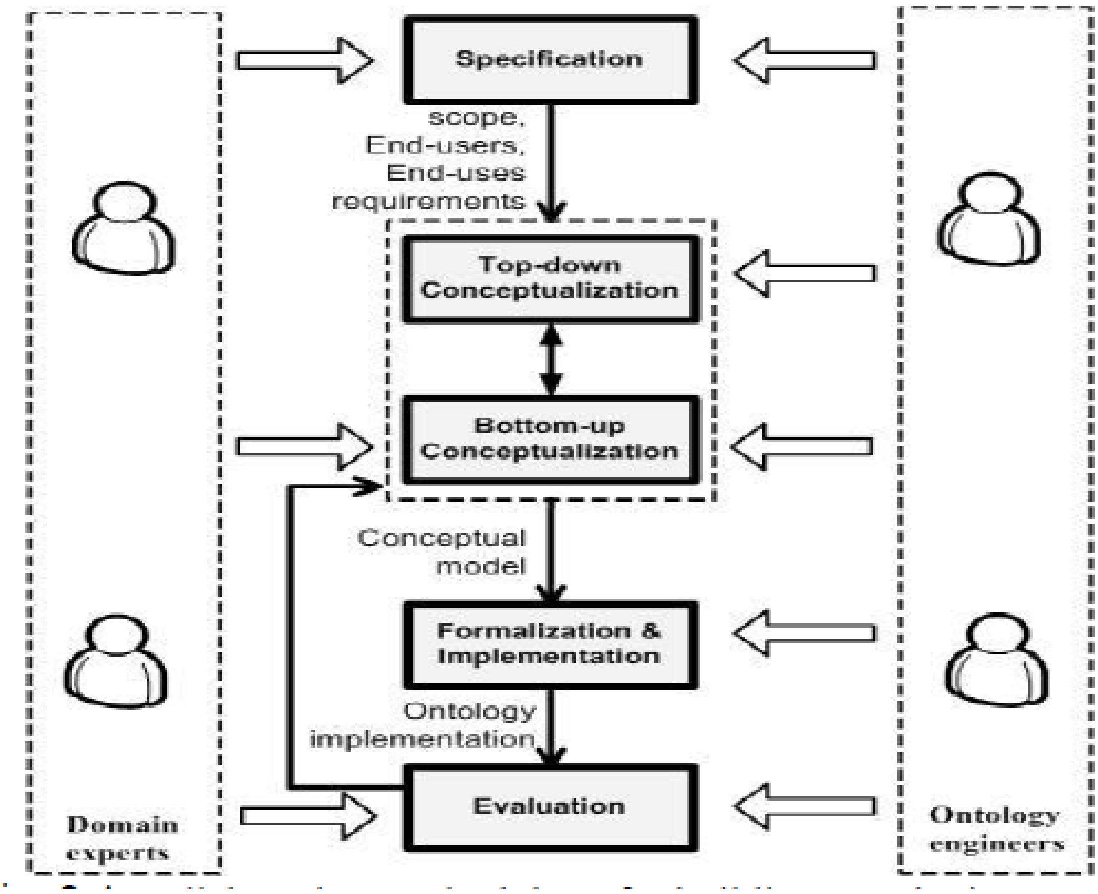


Figure 2: A CM for building ED Ontological Model (EDO) [31]

investigated with the help of domain experts. These sub-sections also emphasize searching for relevant terms at existing non-ontological resources in lexicons, thesauri, taxonomies and linked datasets [31].

3.3.3. Inclusion of Ontology Design Patterns (ODPs)

This phase supports the conceptualization phase, including ODPs, which facilitates the modelling of recurrent scenarios and provides a guideline for correctly incorporating these knowledge sets and linked data sets into DO without any inconsistency and non-coherent behaviour [31].

3.3.4. Formalization and Implementation

This phase is focused on how the conceptual (concepts-relationships) model can be transformed into a commutable model (an explicit form with data rendering form) using semantic web languages, including OWL, resource description framework (RDF), and RDF schema (RDFs)[11]. Here, two activities are needed during the implementation phase, essential to the ontologies' alignment with other models and the re-use of upper ontologies. The alignment activities describe the mechanism of incorporating other models and external ontologies with linked open data (LOD) into DO with the help of identifying matching concepts. The LOD[12] is machine-readable interlinked data on the web (e.g., Convology, disease ontologies) [31].

3.3.5. Evaluation

In this phase, we check developed semantic model fulfils the requirements defined in the specification phase with the help of CQs. Competence questions (CQs) are considered a standard method to assess an ontology's ability to answer such vague questions developed in the specification phase with domain users. We also test some critical concepts of lexicon and vocabulary, hierarchy, taxonomies, semantic relations, context or application, syntax and structure and their architecture using application-based evaluation methodologies [34] and human assessment [35].

4. Results

4.1. KG-Life Cycle: Knowledge Graph Construction Pipeline

The following figure 3 describes a systematic journey of the KG-life cycle and its different phases.

4.2. Knowledge Acquisition (KA) Layer

The KA layer consists of various data acquisition (DA) techniques (e.g., interviews, observations, surveys, archived data and focus groups) gathered from domain experts, health stockholders, physical notes and documents. The DA process can be driven using KA methods such as modelling workshops, and the steps can be seen in detail [26].

4.3. Knowledge Representation (KR) Layer

The KR layer defines a systematic way of constructing ontology in an ontology editor (e.g. protege). In the ontology development (DO) process, we have taken input from the KA layer and drew some concepts, entities, and relationships (Object properties) among concepts, data properties, business rules and class axioms for creating intelligent KBs. It becomes the backbone of any intelligent AI system, especially CAs. This layer is also responsible for maintaining the interlinking of different ontologies and vocabularies, including ODPs[13].

[11] https://www.w3.org/TR/rdf-schema/
[12] https://lod-cloud.net/
[13] http://ontologydesignpatterns.org/wiki/Main$_{p}age$

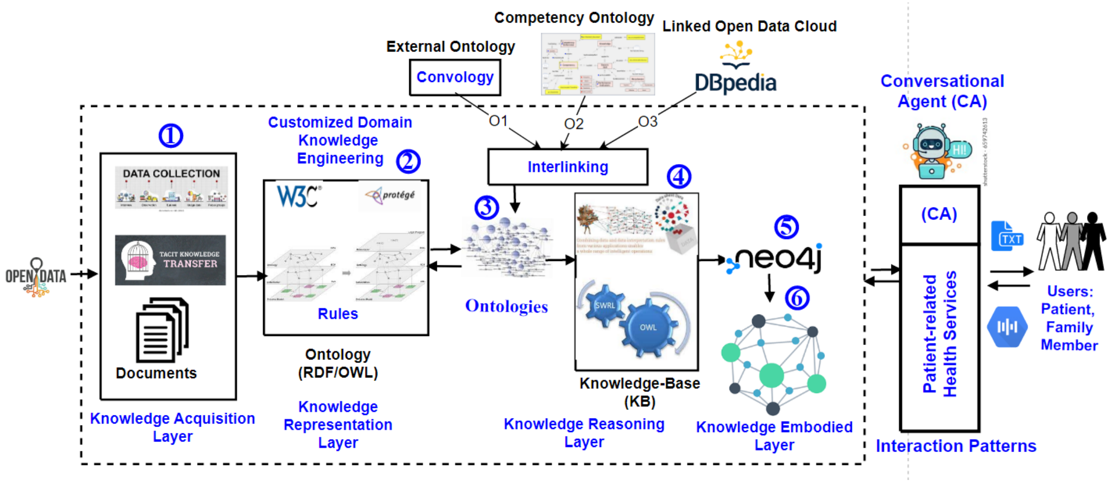


Figure 3: Knowledge Graph Construction Pipeline

4.4. Knowledge Representation and Reasoning (KRR or KR^2) Layer

The KR^2 layer explains the business rules manufacturing and how we can write rules in the ontology editor using SWRL. These symbolic expressions can be integrated with dump KBs to become intelligent and generate new inferences according to the base facts. Generating new inferences is possible because the IE makes the KB more intelligent and gives the information according to the query with optimal answers. The inference engine (IE) is a powerful tool that interprets and evaluates the facts and applies logical rules in the KB to answer. The prominent role of the inference engine is to make knowledge classification, diagnosis inconsistency and non-coherent attitudes among concepts, monitor their relationships etc. In ontology development process. This work uses tools such as IE as a reasoner, such as Pallet and Drools. The Pallet is a built-in plugin used within the Protege environment and recommended reasoner, which takes rules and axioms and generates logical inferences about properties or class definitions.

Similarly, Drools reasoner follows the structure like ((OWL+SWRL⟶Drools[14]) ⟶Run Drools⟶Drools⟶OWL)). This structure explains the first session of the expression transfer SWRL rules and relevant OWL knowledge to the rule engine. The second session defines its execution process, and the third describes the transformation of inferred rule engine knowledge into OWL knowledge. This reasoning ability helps KBs to answer according to query with data inconsistency or lack of coherence.

4.5. Knowledge Embodied Layer (KE)

The KE layer narrates the execution semi-automated way of processing ontology with OWL or RDF extensions parsed through IE and stored into KGs databases such as Neo4J and Stardog. Here, we used Neo4J as a KGs database to store RDF triples of DO and qualify for the KE with inference power. We also used cypher query to get the answer according to our competence

[14]https://www.drools.org/

questions (CQs).

4.6. Context-Aware Domain Ontology (DO): Pediatric Emergency Department Model

This knowledge engineering (KE) aims to develop KG focusing more on the emergency context. This ontological model contains 271 classes, 6242 axioms, 5273 logical axiom counts, 959 declaration axiom counts, 247 object property counts, 26 data property counts, 413 individual counts and six annotation property counts. We have used a formal collaborative methodological approach in figure 4 using ODPs; conversation ontology (e.g. convology[15]), competence ontology and some part of disease ontology to develop the conceptual model resulting in a PEDology[16].

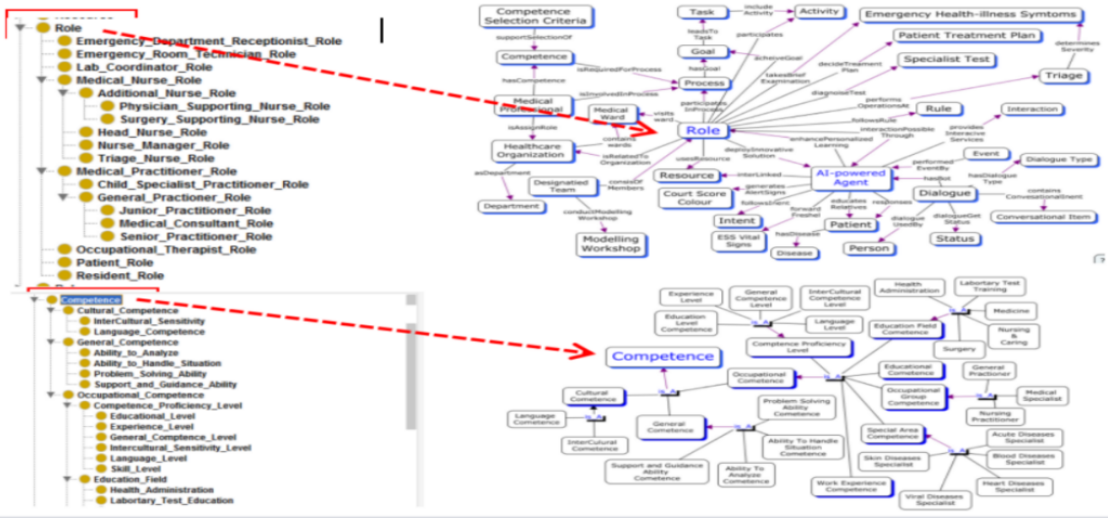


Figure 4: Context-aware Domain Ontological Model of PED (PEDology).

4.7. SWRL: Symbolic Representation of Rules

The table 1 describes the SWRL rules to make the KB more intelligent with reasoning ability. AI systems, especially CAs, are more intelligent by using rules to give query answers reasonably. These rules follow abstract syntax and contain a sequence of axioms and facts. Axioms vary, such as subClass axioms, equivalentClass axioms and extension with rule axioms. The rule axiom consists of an antecedent (body) and a consequent(head), each consisting of a possibly empty set of atoms.

[15]https://horus-ai.fbk.eu/convology/
[16]https://github.com/abid-fareedi/EmergencyDepartmentOntology/blob/main/EDOntology.rdf

Table 1
Context-aware SWRL-Rule Embodied in OWL Model related to ED

	SWRL-Rules
1	Patient_Role(?p)∧has_Disease(?p,"Asthma_Attack") ∧has_Disease(?p, Viral_Infections")∧Role(?R)∧performsAssessment(?R,1st_Stage_Assessment1)⟶isReffered_DiagnosticTest(?R, Latent_Tuberculosis_Infection_LTBI_Test)
2	Patient_Role(?p)∧has_Disease(?p,"Hearing_impairment")∧Role(?R)∧performsAssessment(?R,1st_Stage_Assessment1)⟶isReffered_DiagnosticTest(?p, Audiometery_Test)
3	Person(?p)∧hasCultural_Competence(?p,Language_Comptence_Strong_Level)∧hasGeneral_Competence(?p,Problem_Solving_Ability_Strong_Level)∧hasOccupational_Competence(?p,PED_Surgery)∧performs2nd_Stage_Assessment(?p,2nd_Stage_Assessment1)∧hasWork_Experience_Competence(?p,8-10_Years)-> isAssigned_Role(PED_Medical_Consultant_Surgeon,?p)
4	Conversational_Agent(?CA)∧initiate_Dialouge(?CA, Deliberation)∧initiate_Dialouge(?CA, Information_seeking)∧forwardFresh_Vitalsigns(?CA, RLS)∧forwardFresh_Vitalsigns(?CA, Body_Temperature_Method)∧inter_Linked(?CA, Adaptive_Process_Triage_ADAPT) ⟶makesResponse(?CA, PED_Malin_Braun)

5. Evaluation and Testing

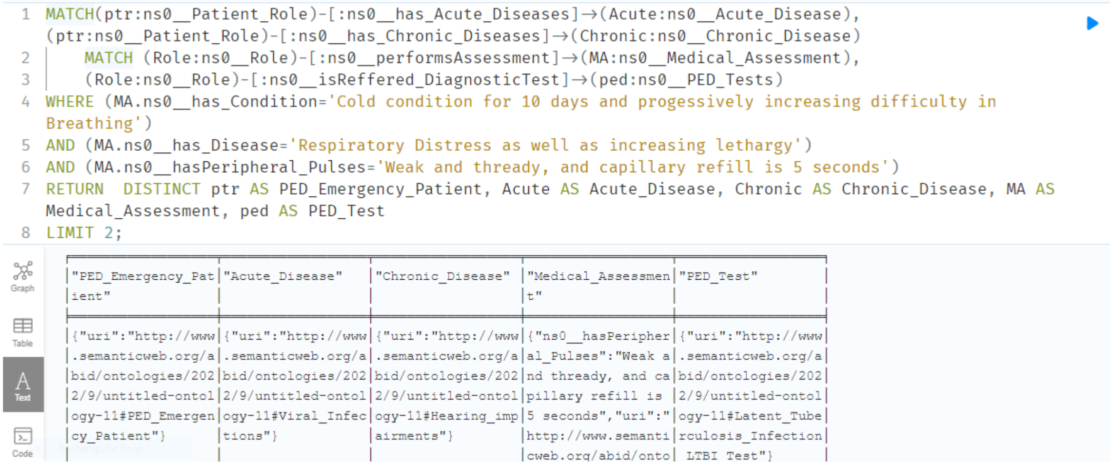
A collaborative methodology that follows an ontological structure is utilized in this section in order to demonstrate the importance of evaluating knowledge graphs (KGs) and ensuring their quality. PEDology was developed based on contributions and discussions from experts throughout the development process. Ontological models are also evaluated at different levels on the basis of structural, semantic-relational, and lexical evaluations.

We use Neo4j[17], a KGs database, to store RDF[18] triples in a structured form. RDF triples is an atomic data entity in the resource description framework (RDF). Our ontological model was imported into Neo4j using the Neosemantics [19]plugin. As a result of 15195 triples loaded and 15590 parsed, the model is parsed, demonstrating the quality and consistency of the loaded model. This work illustrates the semi-automated behaviour of KGs.

5.1. Using Cypher Query Structure in Neo4J

Cypher Query[20] is used in the Neo4J environment, which is the corresponding language for the data access represented in the property graph. It is slightly different from the SPARQL[21] query, which is used to access the data from web repositories shaped in the resource description framework (RDF) format. These languages are much inspired by SQL[22] query structure. The structure of the cypher query can be seen in the figure 5, which follows rule-1 in the table 1.

[17]https://neo4j.com/
[18]https://www.w3.org/RDF/
[19]https://neo4j.com/labs/neosemantics/
[20]https://neo4j.com/developer/cypher/guide-cypher-basics/
[21]https://www.w3.org/TR/rdf-sparql-query/
[22]https://www.w3schools.com/sql/



```
MATCH(ptr:ns0__Patient_Role)-[:ns0__has_Acute_Diseases]→(Acute:ns0__Acute_Disease),
(ptr:ns0__Patient_Role)-[:ns0__has_Chronic_Diseases]→(Chronic:ns0__Chronic_Disease)
    MATCH (Role:ns0__Role)-[:ns0__performsAssessment]→(MA:ns0__Medical_Assessment),
    (Role:ns0__Role)-[:ns0__isReffered_DiagnosticTest]→(ped:ns0__PED_Tests)
WHERE (MA.ns0__has_Condition='Cold condition for 10 days and progessively increasing difficulty in
Breathing')
AND (MA.ns0__has_Disease='Respiratory Distress as well as increasing lethargy')
AND (MA.ns0__hasPeripheral_Pulses='Weak and thready, and capillary refill is 5 seconds')
RETURN  DISTINCT ptr AS PED_Emergency_Patient, Acute AS Acute_Disease, Chronic AS Chronic_Disease, MA AS
Medical_Assessment, ped AS PED_Test
LIMIT 2;
```

"PED_Emergency_Patient"	"Acute_Disease"	"Chronic_Disease"	"Medical_Assessment"	"PED_Test"
{"uri":"http://www.semanticweb.org/abid/ontologies/2022/9/untitled-ontology-11#PED_Emergency_Patient"}	{"uri":"http://www.semanticweb.org/abid/ontologies/2022/9/untitled-ontology-11#Viral_Infections"}	{"uri":"http://www.semanticweb.org/abid/ontologies/2022/9/untitled-ontology-11#Hearing_impairments"}	{"ns0__hasPeripheral_Pulses":"Weak and thready, and capillary refill is 5 seconds","uri":"http://www.semanticweb.org/abid/onto	{"uri":"http://www.semanticweb.org/abid/ontologies/2022/9/untitled-ontology-11#Latent_Tuberculosis_Infection LTBI Test"}

Figure 5: Cypher Query Structure and Retrieved Result from PEDology Model. This figure is the answer to the CQ: *What patients have specific diseases, and who is in charge of assessing them for medical tests in the emergency department?*

Figure 6 explains CA and its interaction behaviour in reality with other concepts in the graph database. This KG structure qualifies, according to rule-4 in the table 1, to become the intelligent KB of AI systems, especially CA, when it interacts with users and gives the answer to their queries reasonably. Its KB must be enriched with reasoning power.

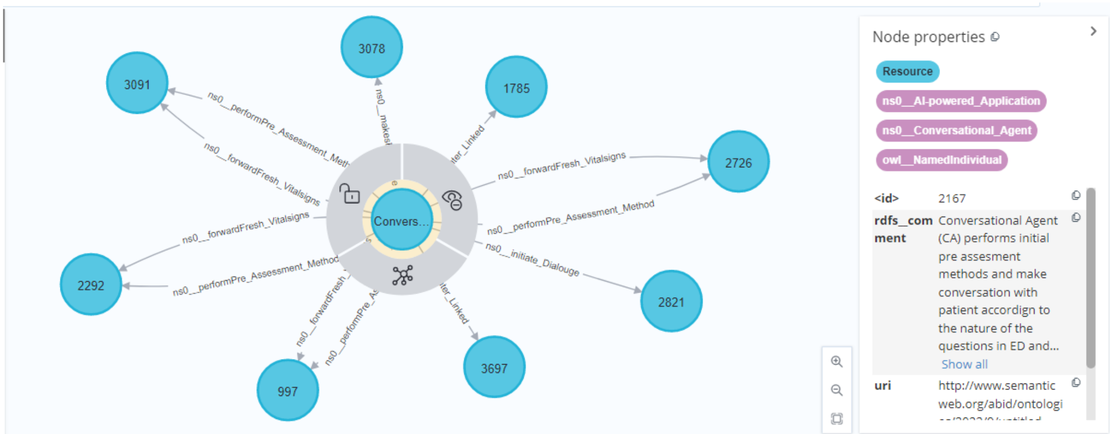


Figure 6: Conversational Agent (CAs) KGs Reflects a Chunk of PEDology Model and answer the following CQ: *How do CAs initiate a dialogue with users, help take vital signs, and refer to triage and operational personnel?*

5.2. Modelling Workshops

We presented the holistic view of the model design to domain exerts during the modelling workshops. It helps us to illustrate how the domain model (ontological model) reflects the discussion related to the PED to the domain experts and also showcases the knowledge engineering mechanism to convert the textual knowledge into structured knowledge. We have also exemplified the domain model of the Karolinska Institute (KI) case with a simple scenario that shows a representation of a practical interpretation of the CA's inclusion in hospital settings. It also illustrates how intelligent AI-based systems incorporate contextual knowledge, and some external knowledge can become an enabler to improve the information flow in a particular context of emergency. We presented and discussed the modelling results to the domain and technical experts to verify the knowledge captured in the model and get feedback for improvement in healthcare settings, especially emergency departments.

6. Conclusion

This study focuses on how KGs can be used as a model to train and evolve conversational applications to facilitate healthcare professionals as coworkers and help smooth interactions between patients and machines for getting on-demand health-related services. We followed a rigorous iterative CRISP-KG approach to aim to develop KGs that depict the domain's contextual knowledge and evaluate a novel onto-logical model artefact. Here, we utilized a recognized collaborative methodology (CM) for designing and implementing the domain ontology of PED (PEDology).

This proposed work gives a state-of-art-work KG (semi-automated) approach to building intelligent CAs that work as a mediator between patients and healthcare users to enable a practical and helpful interaction before or upon arrival at the medical department to address some overcrowding issues. A knowledge graph-driven approach helps to develop AI systems (new kinds of ISs) in healthcare more effectively by providing models reflecting a particular healthcare unit. It helps design and develop intelligent solutions using a KG approach to automate various tasks and processes in the healthcare organization.

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