Digital Health Transformation: Leveraging Knowledge Graphs Reasoning Framework and Conversational Agents for Enhanced Knowledge Management

Abstract. The research focuses on utilizing AI systems, particularly conversational agents (CAs), to optimize information flow procedures within healthcare emergency departments (EDs), especially during peak hours. The authors adopted the Cross Industry Standard Process for Data Mining (CRISP-DM) approach to guide our research into a tailored CRISP-Knowledge Graph (CRISP-KG) methodology. Our approach involves harnessing the power of knowledge graphs (KGs) to construct an intelligent knowledge base (KBs) for conversational agents. This augmentation enhances their reasoning, knowledge management, and context awareness abilities. The development of these robust KBs is facilitated through a collaborative methodology (CM) and the implementation of ontology design patterns to create a formal ontological model. The ultimate objective is to empower conversational agents with intelligent KBs, enabling seamless interaction with end-users and enhancing the quality of care within EDs. Authors leveraged semantic web rule language (SWRL) for inference, utilizing the knowledge graph approach to assist healthcare practitioners and patients in efficiently managing information flow and information provision within EDs. The anticipated outcome is an improvement in care quality and better care outcomes.

Keywords: Knowledge Management, CRISP-KG, Applied Ontologies, SWRL, Knowledge Graphs, Conversational Agent

1. Introduction

In recent times, there has been a notable surge in the integration of artificial intelligence (AI) applications within organizations, particularly in automating the handling of user inquiries in various domains. The primary aim has been to develop intelligent systems capable of emulating human-like conversational interactions while possessing reasoning capabilities [1]. These intelligent systems, often referred to as conversational agents (CAs) or social robots, are essentially sophisticated software programs that employ a combination of machine learning (ML), knowledge representation and reasoning (KRR or KR^2), and management techniques principles to facilitate natural language conversations [2]. In the realm of healthcare, the applications of CAs represent a novel category of information systems (IS). These systems play a crucial role in assisting patients by providing answers to their specific health-related inquiries. Additionally, they serve as social robots, equipped with collaborative capabilities, to aid healthcare professionals in their work [3, 4].

In the contemporary landscape, Conversational AI has emerged as a vibrant and highly dynamic field of research. Its scope spans a broad spectrum, encompassing rule-based conversational systems like ELIZA [5] on one end, to the cutting-edge open-domain, data-driven CAs such as *Apple's Siri*, *Google Assistant,* and *Amazon's Alexa* [1]. On the other end, notably within healthcare, a few conversational AI applications are tailored for specialized, enclosed domains, focusing on various scenarios like hospital emergency departments (ED). These systems follow a variety of techniques, including pattern matching and ontologies [6] from the domain corpora and compute to generate responses without a comprehensive understanding of the conversation. Due to their limited ability to grasp contextual knowledge and draw insights from conversational data specific to particular scenarios, these conversational agents are constrained in their reasoning capabilities.

Conversational agents (CAs) typically possess autonomous capabilities for human-machine interaction (HMI), serving as helpful assistants in both professional workplaces and domestic settings [7]. To effectively model contextual knowledge and account for environmental constraints, sophisticated methods like Ontologies and Knowledge Graphs (KGs) are employed in knowledge modelling cycles [8].

Ontology is recognized as a mechanism for conceptualizing domain knowledge. Its primary function is to provide formal and explicit specifications of shared concepts and their relationships with other entities. Ontology serves to enhance flexibility, reusability, and various other aspects [9]. KGs and Ontologies are often used interchangeably, representing the same fundamental concepts. In the context of KGs, the schema can be effectively defined as an ontology, illustrating the properties of a particular domain and its contextual knowledge, along with the relationships that exist within it [10].

Knowledge representation (KR) plays a pivotal role in advancing context-aware CAs and automating their reasoning processes. The use of ontology-based KRR techniques [11] is highly considered a powerful tool that empowers CAs with intricate domain knowledge, enabling them to perform complex tasks in the realm of social robotics, make informed decisions, and engage with domain users effectively with real-world environment [12].

The research focuses on developing autonomous social robots, such as CAs, to reduce users' time searching for relevant information in hospital settings and improve information flow procedures utilising knowledge-based intelligent CAs. This research proposed a semi-automated approach that helps design the CAs with knowledge reasoning capabilities. This approach leverages semantic web language rules (SWRL[1]), a rule language designed for semantic artifacts, in combination with domain knowledge, including ontologies and external knowledge models, to offer health-related services. These CAs can effectively function as co-workers alongside healthcare professionals (HPs), assisting and automatically addressing user queries while applying reasoning abilities, particularly in emergency unit scenarios.

In addition, this research work emphasizes the importance of context-awareness modelling, a systematic approach to structuring data. The modelled data is subsequently processed, transitioning from high-level situational information to low-level situational details during the reasoning phase. As a result, end-users can access and retrieve information through sophisticated knowledge graphs (KGs) [13].

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

For a more comprehensive understanding of the contextual knowledge specific to the pediatrics emergency department (PED), the relevant information can be found in (*see section 3.1*), and a detailed case study is provided [14].

This paper structure comprises the following sections: Section 2 offers a concise review of desktop research, covering topics related to ontologies, KRR or KR[2] techniques, KGs for AI systems, and context-aware rules. Section 3 presents the methodology, including a detailed case study, customized CRISP-KG approach applied in the research design process, and the collaborative methodology (CM) incorporating ontology design patterns (ODPs). Section 4 provides a comprehensive presentation of the study's results and thoroughly discusses the findings. Section 5 explains the evaluation procedures and testing results. Section 6 offers a conclusive summary of future work.

2. Theoretical Background

As a branch of symbolic AI, knowledge-based (KB) systems are based on a specific domain of interest where symbols surrogate real-world entities such as physical objects, events, relationships, and others. This representation is manifested in the design of artifacts, typically in the form of models, initiations or prototypes [15].

2.1. Ontology

This research work integrates diverse classes of ontologies, encompassing domain ontologies that encapsulate contextual knowledge pertaining to the emergency departments (EDs)—convology[2] an ontology tailored for conversational agents (CAs), developments, personal profile ontologies that encompass competencies and corresponding skill sets and also integrates ontology design patterns (ODPs) as external knowledge.

Healthcare Ontologies can be classified into three groups based on the type of knowledge they incorporate [16-17]. The first group comprises the standard medical terminologies aimed at ensuring consistency across various healthcare information systems (HISs). Examples of ontologies in this group include the ICD-10[3] ontology [18-19], SNOMED-CT[4]

[2] https://horus-ai.fbk.eu/convology/
[3] https://bioportal.bioontology.org/ontologies/ICD10/
[4] https://www.snomed.org/

[20], the FMA[5] [21] and ICNP[6] [22]. The second group encompasses declarative knowledge pertaining to the constant concepts and relationships within a medical organization or the field of medical research. For instance, the *Actor profile ontology* includes competencies and skill sets to identify positions and responsibilities within the healthcare context [17].

The third group encompasses procedural knowledge, identifying the terms, decisions and processes governing workflow management in emergency departments (EDs). Examples within this category include instruction ontologies used in evidence-based clinical decision support systems, such as those related to Triage [17]. Among these three groups, ontologies, including the *International Classification of Diseases* (ICD), SNOMED-CT standards, the *Foundational Model of Anatomy ontology* (FMA), and the *International Classification for Nursing Practice* (ICNP), are widely recognized and extensively employed in related research. They are pivotal in data integration and knowledge sharing among healthcare stockholders. Their primary objective is to enhance the optimization of information flow procedures and improve the provision of information within emergency units [23].

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

Knowledge representation (KR) is a specialized field within artificial intelligence (AI) dedicated to capturing real-world information for solving complex problems. Its primary aim is to structure and organize domain knowledge with critical attributes, including accuracy of representation, adequacy of inference, efficiency of inference, and efficiency of acquisition, to render it more coherent and rational, ultimately delivering substantial impact. Numerous KR approaches have been explored, such as Logical representation (LR), Procedural representation (PR), Network representation (NR), and Structured representation (SR). Knowledge Representation and Reasoning (KRR) aims to design AI systems capable of reasoning with the machine-interpretable representation of the domain knowledge, much like human reasoning processes that manipulate these symbolic representations [24].

In adherence to the Semantic Web (SW) technology standards, domain knowledge appears in different forms, with a significant focus on semantic networks, production rules, and logic [24]. The semantic networks are conceptualized as graphs, where nodes correspond to concepts, and arcs denote relationships between these concepts, adhering to a triplet structure, for example:

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*) [25].

Knowledge representation (KR) serves as a critical foundation for constructing AI-driven applications and expert systems (ES) with reasoning capabilities, particularly when developing agents. Knowledge bases (KBs) used in these systems draw their information from human experts and a repository of business production rules. Initially, the knowledge is often incomplete and uncertain. Therefore, there is a need to enhance its logical consistency. Specific rules are employed to link facts with associated confidence factors to achieve this.

Additionally, KR follows particular methodologies, such as forward-chaining and backwards-chaining algorithms, to facilitate the reasoning processes [26]. AI system development relies on a spectrum of knowledge types: structural, heuristic, meta-knowledge, factual, implicit, explicit, tacit, declarative (*conceptual*), and procedural knowledge. Among these, declarative and procedural approaches are pivotal in designing knowledge-based agents. Declarative knowledge is conveyed through declarative sentences, while procedural knowledge encodes desired actions or behaviours within these agents [25].

2.3. Knowledge Graph for AI Systems

The construction of applied ontologies represents a crucial phase in developing knowledge graphs (KGs) for AI-based System development. An ontology serves as a blueprint for a knowledge graph schema, elucidating the characteristics of a specific domain and its intricate interconnections. Ontology is recognized as a valuable and creative tool that plays a vital role in knowledge acquisition (KA), management, and transforming knowledge into various data-rendering machine-readable formats [27]. Recent research on KGs has gained significant attention in academia and industrial circles, particularly for AI

[5] https://bioportal.bioontology.org/ontologies/FMA
[6] https://bioportal.bioontology.org/ontologies/ICNP

applications such as recommendation and fraud detection [10]. Furthermore, the incorporation of diverse business or domain rules has transformed it into a specialized field of AI, particularly in the development of intelligent knowledge base (KB) systems, CAs, games, health information systems (HIS) and decision support systems (DSS), especially in the healthcare sector.

This research emphasizes knowledge reasoning using rule-based logical methods, particularly in knowledge acquisition and representation that reflects domain knowledge, especially in healthcare. The authors tailored various applied ontologies to cater to the needs of healthcare practitioners. These applied ontologies encompass areas such as competence, as seen in competence ontology [28]; conversational interactions, exemplified by Convology [29]; disease, as addressed by the disease ontology[7]; and domain-specific ontology meta models related to ED context for the development of the intelligent CAs' knowledge base (KB). These customized ontologies, combined with rule-based methods, play a pivotal role in developing AI-based systems (e.g., social robots, chatbots, recommendation systems, etc.), notably conversational agents (CAs) within the healthcare domain.

2.4. Context-Aware Production Rules

In most cases, the knowledge representation (KR) typically combines both implicit and explicit knowledge, accessible to both users or machines through the inference process and formalized into different forms, including symbols, frames, semantic networks, conceptual graphs, inference rules and sub-symbolic patterns [30]. The construction of context-related production rules written with the consensus of domain experts and users helps develop a variety of CAs endowed with inference capabilities, enabling them to provide optimal responses to queries [31]. Furthermore, KR is recognized as a methodology for encoding knowledge within intelligent systems knowledge base (KBs), primarily employing three primary reasoning techniques: ontology-based reasoning, case-based reasoning and rule-based reasoning [32].

Rule-based reasoning 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[8] 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 a positive conjunction of zero or more atoms and does not support negative atoms or disjunction [33]. 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 [24]. SWRL schema can be seen in various formats, such as XML[9] 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. Ontology designing editors (*e.g., protege[10], TopBraid Composer[11] etc.*) are used to construct ontology or dump KBs. The authors followed various ontology reasoners (*e.g., Pallet[12], Ontop[13], Hermi[14], etc.*) to make it more sensible and rational. The authors represent domain knowledge in symbolic statements and rule-based formalization.

3. Methodology

3.1. The Karolinska University Hospital Case

This research is grounded in real-time observations conducted within the Pediatric Emergency Department (PED) of Karolinska Hospital in Solna, Stockholm, Sweden. To gain valuable insights, the authors engaged in modelling workshops involving a diverse group of experts from various disciplines within the hospital. Our approach, as outlined in specific steps [34], was to foster effective communication among domain users, medical professionals, and experts responsible for emergency patient treatment procedures and explain emergency department (ED) workflows. Initially, the authors conducted thorough observations and endeavoured to reverse engineer the entire workflow within ED. Our

[7] https://disease-ontology.org/community/use-cases

[8] https://www.w3.org/OWL/
[9] https://www.w3.org/XML/
[10] https://protege.stanford.edu/
[11] https://franz.com/agraph/tbc/
[12] https://www.w3.org/2001/sw/wiki/Pellet
[13] https://www.w3.org/2001/sw/wiki/Ontop
[14] http://www.hermit-reasoner.com/

goal was to comprehensively analyze the processes and information flows associated with the admission and treatment of patient upon their arrival at the PED.

After careful assessment and consensus-building, the authors identified several critical issues associated with patient-centric treatment procedures. Our ultimate objective was transitioning from the "*As-Is*" situation to an envisioned "*To-Be*" situation within ED. Drawing from extensive desktop research, it was evident that there had been a consistent annual increase of *75%* in inpatient visits to the ED. Consequently, affected patients often encountered unexpected challenges such as prolonged waiting times and issues related to overcrowding issues[15] [35].

From the *Hospital's perspective*, a smooth functioning of the ED is pivotal as it directly impacts the overall activities and workflows within the emergency unit. Therefore, the ED must be well-organized. To ensure patients receive timely and appropriate medical assistance, the Hospital deploys specialized information systems (IS) that are classified.

These IS include Triage, which functions as a decision support system (DSS), as well as electronic health records (EHR), and electronic medical records (EMR). EHR system focuses on the patient's comprehensive health profile and facilitates information sharing among healthcare practitioners. Meanwhile, the EMR contains each patient's detailed medical and treatment history. Triage, in particular, plays a promising role in prioritizing patient patients for care and treatment.

However, challenges arise when a substantial influx of patients and long waiting queues lead to a bottleneck at the Triage in the ED. To address these challenges, the implementation of supportive technological solutions becomes essential. Conversational agents (CAs), including chatbot social robots, have emerged as valuable tools. They enhance various front-end Triage procedures, especially in dealing with practice inconsistencies. CAs also reduce the substantial patient load in the waiting room, especially during peak hours in the ED. Additionally, they initiate streamlined operations to improve communication and break down data silos within different departments and treatment areas [35].

From the *Patient's perspective*, the long waiting times in the ED, often coupled with heightened high anxiety, can erode their trust in healthcare services. When EDs operate poorly, it jeopardises individual patients' health and safety and undermines public confidence in the healthcare system.

3.2. Customized CRISP-KG Approach for Research Design Process

In this research, the authors have employed a tailored CRISP-KG approach, which draws inspriations from the *Cross Industry Standard Process for Data Mining* (CRISP-DM) approach [36]. The aim was to design a research process and evaluate a novel artifact incorporating competence questions (CQs) pertinent to the emergency department context. The expected outcome of a CRISP-KG study is the creation of artifacts in the form of knowledge graphs (KGs), that encapsulate the discourse related to the ED. This approach involves a series of well-defined steps, including business understanding, data understanding, data preparation, the design of KGs model, KGs creation and upgradation, evaluation and deployment. These steps collectively ensure a methodical and structured research design process.

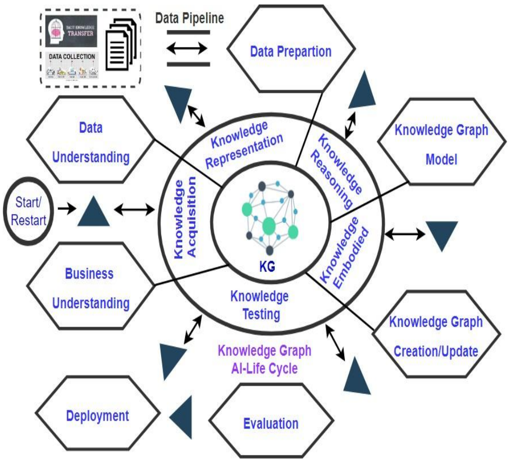


Fig. 1. Customized CRISP-KG Approach for Research Design

The stages of business and data understanding are interlinked with the knowledge acquisition (KA) layer, which is responsible for gathering data from diverse sources and facilitating the transition of various data to the subsequent data preparation stage. Fig. 1. illustrates the execution of these steps.

In the *Data preparation (DP) stage*, data is transformed into a lightweight database known as called taxonomies. Subsequently, this data undergoes conversion into an ontological model referred to as the

[15]https://www.usacs.com/services/case-studies/organizational-transformation-at-a-pediatric-emergencydepartment

heavyweight model, aligning it with the knowledge representation (KR) layer.

Similarly, in the *Knowledge graphs (KGs) model stage*, business production rules guide the transformation of semantic web rule language (SWRL) rules into the web ontology language (OWL) model, rendering it more logical and intelligent and linking it to the knowledge representation and reasoning (KRR) layer.

The *Knowledge graphs (KGs) creation and upgradation stage* is managed by the knowledge engineering (KE) layer, where business rules are parsed through information extraction (IE) and stored within KGs.

During the *Evaluation stage*, KGs are rigorously assessed against competence questions (CQs) and linked to the knowledge testing (KT) layer to ensure the effectiveness of the ontological model within KGs creation.

The *Deployment stage* involves development and delivery to developers who will create various health-related services. These services aim to facilitate healthcare professionals (HPs), patients, and their families within the ED context.

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

There are several mature ontology development methodologies, such as Methonotology [37], *Toronto Virtual Enterprise* (TOVE) [38], On-To-knowledge [39], DILIGENT [40], and NeOn [41] are available for ontology development and tools (*e.g., Protege, Topbraid Composer*) to create the semantic model by using the W3C standards. 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 research work followed collaborative methodology (CM) to define concrete steps for developing domain ontology (DO) of ED related to the healthcare sector [42].

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**[16]** [43], implementation and evaluation [42]. The following fig. 3. demonstrates a systematic way of these steps for better realization. The authors followed certain steps of CM and constructed a semantic model of PEDology for organizing the information flow within the healthcare context in EDs. This model has proposed a combined approach to evaluate the designated model.

3.3.1. Specification

This phase defines the study's scope and requirements, which form a fundamental component of developing semantic models, including taxonomies and ontological models. The ontology modeller collaborates closely with domain experts during modelling workshops to accomplish this. In these workshops, the ontology modeller identifies the essential information pertinent to the specific domain in conjunction with domain experts. This identified information is then incorporated into the semantic model using various data acquisition (DA) techniques, including modelling techniques [43]. Domain experts actively contribute their insights and feedback through various methods, including brainstorming sessions, interviews, and questionnaire completions.

Fig. 2. illustrates and defines different agents (roles), such as conversational agents (CAs), doctors/physicians, patients, and family/caregivers. This system is categorized into two levels: first-level users interact with the front-end systems with text and verbal communication capabilities with login authentication use-case. After making login authentication, conversational agents (CAs) interlink with different use cases that provide different health-related facilities and services concerning healthcare professionals (HPs) and patients, forward fresh, vital signs, and recommend medicine. Similarly, the second-level users, doctors/clinicians interact with various use cases, including checking patient medical history, patient critical values configuration, adding business rules or production rules, medical assessment, and making a diagnosis and recommendations. The proposed systems offer these healthcare services. The patients are also interlinked with use cases, especially

[16] http://ontologydesignpatterns.org/wiki/MainPage

real-time health data monitoring, personal health records, and medication reminders. The proposed solution in this research work provides these use case facilities. In the end, family/caregivers are also facilitated by the system using use cases such as viewing activities and tracking patient status regularly. Fig. 2. gives the abstract view of the AI-powered conversational agent and illustrates the behaviour and functionality of the system.

This activity transforms the refined requirements list into a final set of competence questions (CQs). This approach, first described in [44], is a widely used method for specifying ontology functional requirements. These questions are crucial for guiding the ontology development process since the ontology in its complete version must be capable of answering them [45].

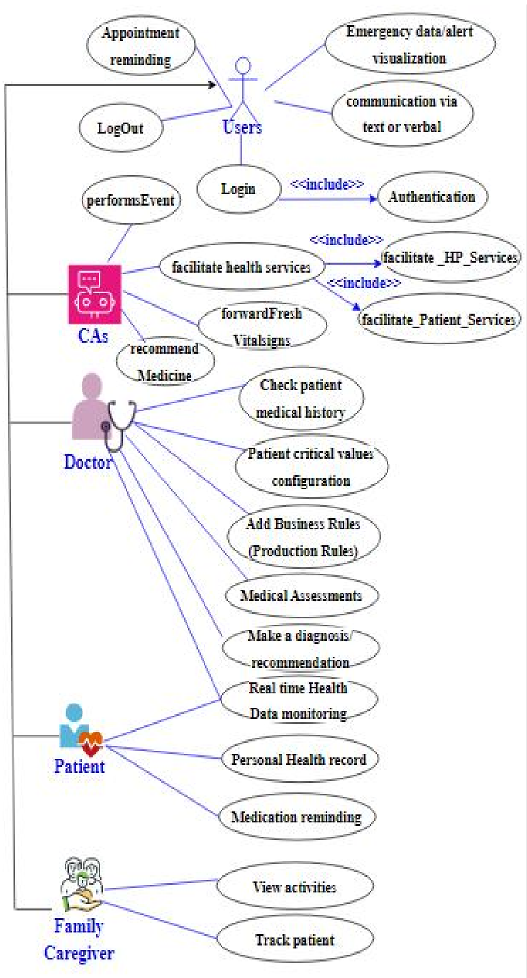


Fig. 2. Use cases diagram of autonomous conversational agent within PED context

Table 1. Proposed Competence Questions (CQs) for PED Case Study

CQ1: What patient have specific diseases?
CQ2: Who is responsible for performing medical assessment in emergency department?
CQ3: What roles are referred for diagnostic test during assessment in emergency department?
CQ4: How conversational agent initiate dialogues in emergency unit?
CQ5: How conversational agent generate alert signal during assessment in case emergency?
CQ6: How conversational agent interlinked with other resources?
CQ7: What type of the services offered by conversational agent to healthcare professionals within emergency unit?
CQ8: What type of the services offered by conversational agent to patients within emergency unit?

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 subsections 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 subsections are instrumental in identifying the most appropriate semantic models and ontologies for potential reuse within the target domain ontology (DO). Collaboration with domain experts is crucial during this phase to ensure that the chosen models and ontologies align with the specific domain requirements. Furthermore, the process emphasizes the exploration of relevant terms beyond ontological resources. These subsections also emphasize searching for pertinent terms at existing non-ontological resources and entails scouring non-ontological sources, such as lexicons, thesauri, taxonomies, and linked datasets [42], to enrich the conceptualization process [42].

3.3.3. Inclusion of Ontology Design Patterns (ODPs)

This phase complements the conceptualization phase by incorporating ontology design patterns

(ODPs). These patterns serve as tools to streamline the modelling of recurring scenarios, offering guidance on seamlessly integrating these knowledge sets and linked data into the domain ontology (DO) while ensuring consistency and coherence [42].

3.3.4. Formalization and Implementation

This phase concentrates on the transformation of the conceptual model, which encompasses concepts and their relationships, into a computable model (*an explicit form with data rendering form*) with explicit data representation. This transformation is achieved through the utilization of semantic web languages, including including OWL[17], resource description framework (RDF)[18], and RDF schema (RDFs)[19]. During the implementation phase, two crucial activities are undertaken to ensure the alignment of ontologies with other models and the effective reuse of uppor ontologies.

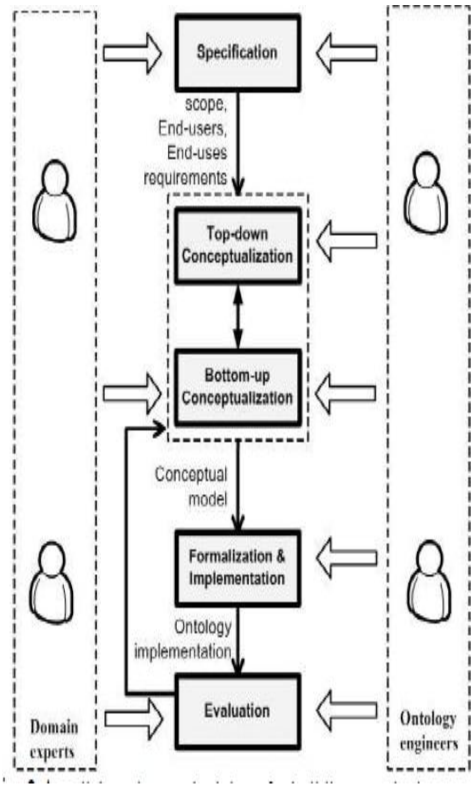


Fig. 3. A Collaborative Methodology for building Emergency Department based Ontological Model (EDO) [42]

[17] https://www.w3.org/OWL/
[18] https://www.w3.org/RDF/
[19] https://www.w3.org/TR/rdf-schema/

The alignment activities describe the mechanism of incorporating other models and external ontologies, particularly those within the realm of linked open data (LOD)[20] into domain ontology (DO). This is achieved by identifying matching concepts, ensuring that the domain ontology is seamlessly incorporated with external resources. In this context, the LOD represents machine-readable, interlinked data accessible on the web, such as *Convology, and disease ontologies* [42].

3.3.5. Evaluation

In this phase, the authors developed the semantic model to meet the specifications outlined in the specification phase with the help of CQs. Competence questions (CQs) are recognized as a standard approach for evaluating an ontology's capacity to address the ambiguous questions crafted during the specification phase in collaboration with domain users. Furthermore, this phase involves rigorous testing of crucial elements, including concepts of lexicon and vocabulary, taxonomies, semantic relationships, context or application relevance, syntax and overall structure. These aspects are evaluated through application-based evaluation methodologies [46] as well as human assessment [47].

4. Systematic Architecture for building Knowledge Graphs

4.1. KG-Life Cycle: Knowledge Graph Construction Pipeline

The knowledge graphs (KGs) life cycle is recognized as a systematic approach to constructing and maintaining KGs, which are considered a powerful tool for representing and organizing structured information which can be easily processed and analyzed by machines. The following fig. 4. describes a systematic journey of the KG-life cycle and its different phases. The KG Life Cycle is dynamic, as knowledge graphs are not static entities but evolve over time. The construction of KGs plays a pivotal role in developing various applications, including search engines, recommendation systems, data integration, and semantic web technologies, enabling a deeper understanding of complex relationships within data targeting multiple industries, especially the healthcare sector..

[20] https://lod-cloud.net/

4.2. Knowledge Acquisition (KA) Layer

The knowledge acquisition (KA) layer consists of diverse data acquisition (DA) techniques, including interviews, observations, surveys, examination of archived data, and the facilitation of focus groups. These techniques are employed to collect information from various sources, including domain experts, stakeholders in the health sector, physical documents, documents, and written records. The data acquisition (DA) process can be driven using KA methods, including activities like modelling workshops. For a more comprehensive understanding of the steps involved in this process, one can refer to the detailed description provided in [34].

4.3. Knowledge Representation (KR) Layer

The knowledge representation (KR) layer established a structured, systematic approach for building ontologies within an ontology editor like Protege. In the ontology development (DO) process, insights gathered from the knowledge acquisition (KA) layer are utilized to define concepts, entities, relationships (*Object properties*), data properties, business production rules, and class axioms. These elements collectively form the foundation for creating intelligent knowledge bases (KBs), which becomes the backbone of various smart AI system, especially CAs. Additionally, the KR layer ensures the seamless interconnection of diverse ontologies and vocabularies, including ontology design patterns (ODPs). This integration facilitates the harmonious coexistence and interoperability of knowledge structures and resources.

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

The knowledge representation and reasoning (KR2) layer provides insights into how business rules are formulated and implemented, mainly through semantic web rule language (SWRL) within ontology editors. These symbolic expressions are then seamlessly integrated with existing knowledge bases (KBs) to enhance their intelligence and enable the generation of new inferences based on underlying facts. The capacity to generate new inferences is a direct result of the inference engine (IE). This potent tool interprets and assesses facts within the KB while applying logical rules to provide answers. The prominent role of the inference engine is to make knowledge classification, diagnosis inconsistency, and non-coherent attitudes among concepts monitor their relationships among concepts. In the ontology development, tools such as IE are employed as reasoners, with examples like Pallet and Drools. Pallet serves as a built-in plugin within the Protege environment and is a recommended reasoner. It excels in taking rules and axioms and generates logical inferences concerning properties or class definitions, enhancing the overall intelligence and functionality of the knowledge bases.In a similar way, the Drools reasoner follows a structured framework: *((OWL+SWRL→Drools) → Run Drools → Drools*[21] *→ OWL))*. This framework elucidates the flow in three distinct sessions:

- ***Expression transfer*****:** In this first session, SWRL production rules and relevant OWL knowledge are transferred to the rule engine, effectively bridging the gap between ontology and rule-based reasoning.
- ***Execution process:*** the second session outlines the execution process within Drools, where production rules are applied, and inferences are made based on the input data and knowledge.
- **Transformation:** The third session focuses on the transformation of the knowledge inferred by the rule engine back into OWL knowledge. This step ensures that the newly acquired insights are seamlessly integrated into the ontology.

This reasoning capability significantly enhances the knowledge base (KBs), enabling them to respond effectively to queries, even in scenarios where there may be data inconsistencies or lack of coherence.

4.5. Knowledge Embodied Layer (KE)

The knowledge embodied (KE) layer narrates the execution process of semi-automated ontology processing using OWL or RDF extensions, which are parsed through an inference engine (IE) and subsequently stored in KGs databases such as Neo4J[22] and Stardog[23]. In this context, Neo4J serves as the KGs database of choice for storing RDF triples derived from the domain ontology (DO), thereby endowing it with inference capabilities. The utilization of Neo4j enables efficient querying and retrieval of information to answer competence questions (CQs). Cypher queries extract answers

[21] https://www.drools.org/
[22] https://neo4j.com/
[23] https://www.stardog.com/

aligned with CQs, providing valuable insights and knowledge-driven responses.

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 a substantial structure, including 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. To construct this KG, a formal and collaborative methodological was, as illustrated in fig. 4. This approach utilized ontology design patterns (ODPs) and incorporated elements from various sources, such as conversation ontology (*e.g., Convology*), Competence ontology and segments of Disease ontology to develop. This result is a comprehensive conceptual model known as PEDology[24]. This meta model provides a structured representation of knowledge specific to the emergency department context.

5. Experimental Results

5.1. PED Ontology (PEDology)

The pediatric emergency department (PED) ontology (PEDology), as shown in Fig. 4. is a comprehensive modular-based approach used to construct multidisciplinary ontology development by merging, aligning, and extending predefined ontologies. This section provides an overview of the generic procedure for building the PEDology. It details its essential components and elements and highlights the main features: the predefined and extended concepts are described in detail. This section also explains in detail the validity of the proposed PEDology. To facilitate understanding, Fig. 5 presents the main components and development stages of the PEDology systematically.

5.2. Design and Conception

In Fig. 4., the authors explain the knowledge graph (KG) construction pipeline and its sequential steps, emphasising the system architecture required for developing conversational agents. This section further expounds upon the generic architecture of PEDology, which can be delineated in two phases. The initial step encompasses a comprehensive discussion, drawing insights from the case study and direct observations (*see section 3.1*), elucidating the rationale and motivation behind adopting a modular architectural approach. The subsequent step entails a detailed presentation of the basic steps in creating PEDology.

5.3. Modular Ontology

In developing ontology-based AI systems, the modularity factor is crucial and highly recommended for developing ontology in multidisciplinary applications such as the proposed ontological systems that could be the basis for developing the conversational agent. For this reason, PEDology combines predefined applied ontologies: Convology, domain ontology with contextual knowledge, diseases ontology, competence ontology, PED service ontology, and using ontology design patterns (ODPs).

The Convology ontology is specifically designed to empower conversational agents (CAs). These agents rely heavily on natural language processing capabilities to comprehend users' intentions through open text. Recent advancements in conversational agents have underscored the importance of furnishing them with background knowledge to enhance their overall effectiveness and efficiency.

Integrating this background knowledge with semantics will significantly expand a conversational agent's capabilities. This augmentation allows for deploying more resilient systems and sustaining structured and meaningful conversations.

On the other hand, the domain ontology (a metadata model) is intricately connected to the context of PED (Pediatric Emergency Department). It is constructed based on insights from the case study, direct observations, and an extensive review of relevant literature. This domain ontology defines the roles fulfilled, the activities governed by various tasks, and the types of services offered by conversational agents, particularly in the realm of healthcare professionals (HPs) and patients.

The disease ontology is utilized extensively in biomedical and bioinformatics research. It aims to build other biomedical ontologies using reuse disease ontology terms or IDs or map to DOIDs as ontology cross-references, synonyms or annotations. In this section, the authors utilized disease ontology in our proposed PEDology work. The authors used competence ontology in the proposed PEDology,

[24] https://github.com/abid-fareedi/EmergencyDepartmentOntology/blob/main/EDOntology.rdf

which describes different competencies of roles in terms of cultural competence, educational competence, general competence, occupational competence, work experience competence, etc. The PED service ontology describes various services CAs offer concerning HPs (e.g., CAs facilitate multidisciplinary clinicians as a co-worker in panic situations) and patients (*e.g., CAs help with patient appointments and rescheduling confirmation*). the authors also customized different ontology design patterns and aligned them within the proposed PEDology as a reuse work in Fig. 5.

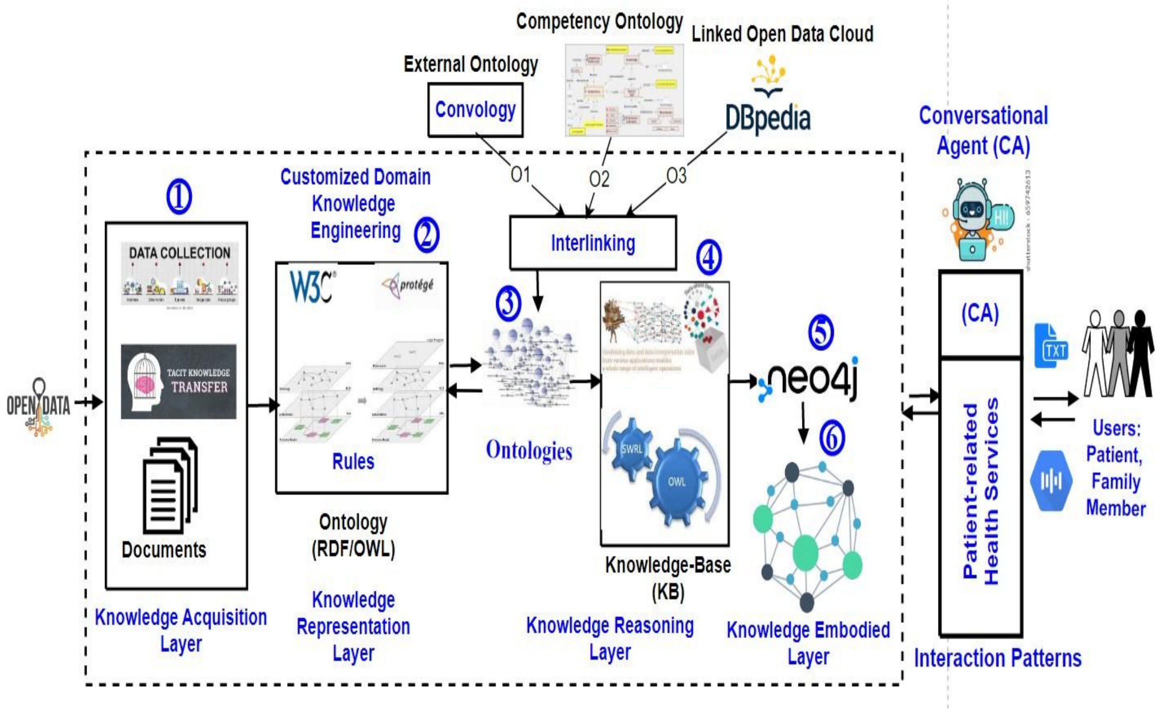


Fig. 4. Knowledge Graph Construction Pipeline and System Architectural Artifact

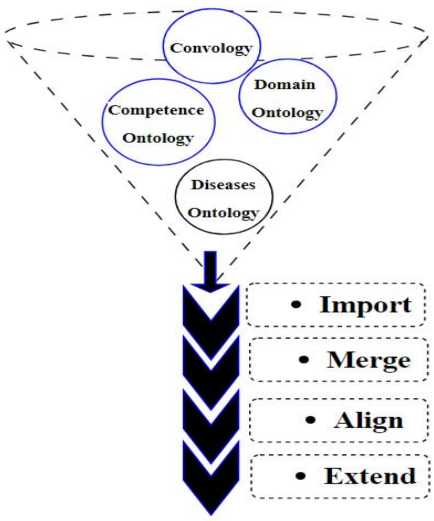


Fig. 5. Systematic approach for the development of PEDology

5.4. Merging, Aligning and Extending Ontologies

Fig. 5. provides a conceptual view of the process involving the phenomenon of importing, merging, aligning and extending within the proposed PEDology. As previously mentioned, predefined ontologies serve as the foundational building blocks for constructing a proposed ontology that accurately captures the context of the emergency department. Various operations are performed to extract all the necessary entities required for this endeavour. In particular, the merging process incorporates external source ontologies into the proposed ontology, thus enabling the reuse of existing work. For instance, Disease Ontology (DOID) is imported as part of this merging process.

5.5. Different Operations of Import, Align, Merge and Extended for Metadata Model of Generated KGs

The monolingual alignment procedure makes the correspondence between each two entities having the same name. This alignment procedure provides a complete association link between all equivalent entities from all ontologies. Similarly, for the merging operation, the mapping phenomenon is followed by a merging operation based on a set of axioms expressing the equivalence.

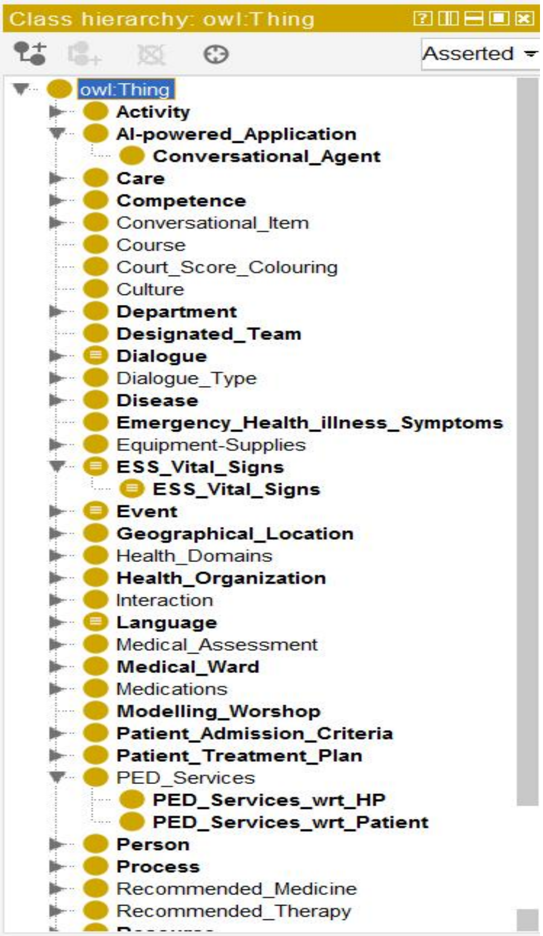


Fig. 6. Taxonomy of the different entities in PEDology Ontological Metadata Model

Ultimately, the mapped and merged ontology must be extended to achieve specific requirements. For example, a Triage nurse is used to operating with CAs. CAs are responsible for initiating conversations with patients to get some preliminary assessment before referring to the Triage and also help take vital signs from the patient upon arrival in the emergency unit. In this section, the proposed ontology contains a set of personalized data properties, object properties, and inference production rules written in semantic web rule language (SWRL) (*see Table 4.*) according to the specific requirements extracted from the case study. The taxonomy of the different entities in the proposed PEDology can be seen in Fig. 6.

5.6. PEDology Visualization

In this section, the authors have presented a chunk of the proposed PEDology in graphic format in Fig. 6 and Fig. 7.

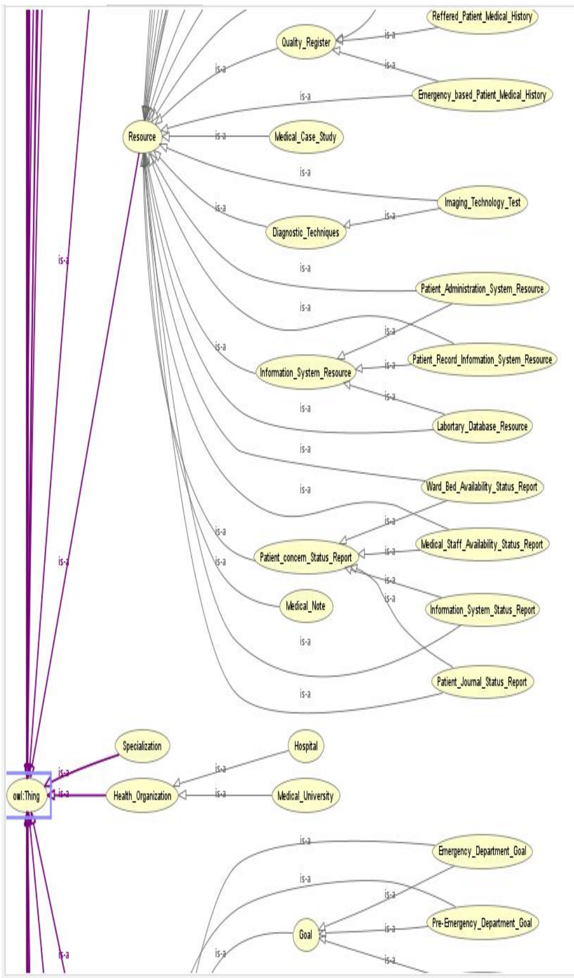


Fig. 7. PEDology Visualization (The chunk of PEDology)

These graphical depictions serve to establish the taxonomies of various entities and illustrate their hierarchical structure, highlighting the "is-a" relationships that exist between parent class and child classes. For instance, under the broader category of "*Resource*," we can observe subcategories such as "*Medical Case Study*" and "*Diagnostic Techniques*," which further break down into "*Imaging Technology Tests*". Another branch includes "*Information System Resources*," which is subdivided into "*Patient Administration System,*" "*Patient Record Information System,*" "*Laboratory Database,*" "*Patient Concern Status Report,*" and "*Medical Notes,*" among others.

This proposed semantic model of PEDology combines the different entities and their taxonomies, which contain "*is-a*" and "*has-a*" relationships for associating various entities. Here, the autors utilized personalized data properties for specific classes or entities and object properties with association links for better expressiveness and semantic understanding.

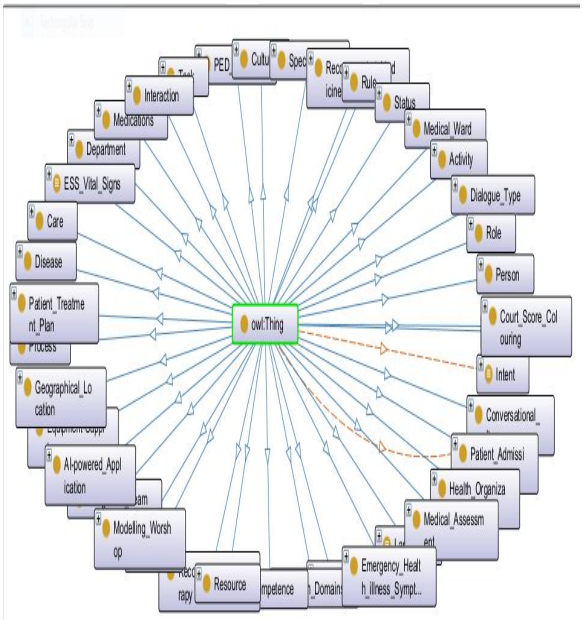


Fig. 8. Graphical representation of the PED ontology (PEDology) semantic model

5.7. PEDology Validation

In this research, the authors incorporated validated, consistent and coherent ontologies such as Convology and Disease ontology and seamlessly integrated them into the proposed PEDology. To enhance the authenticity and coherence of our work, the authors conducted ontology consistency tests. These tests were carried out using the "*Ontology Debugger*" plugin within ontology editing tools such as Protege, as illustrated in Fig. 9.

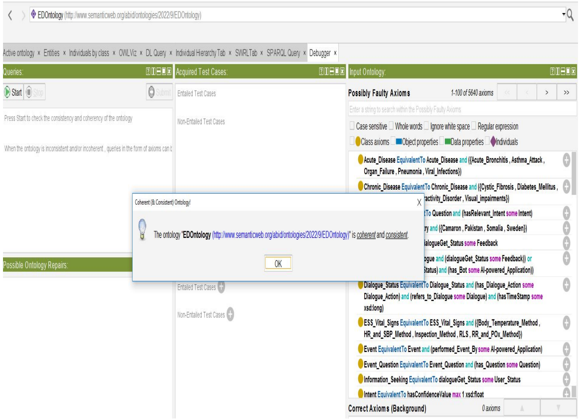


Fig. 9. PED ontology (PEDology) Validation Test

5.8. SWRL: Symbolic Representation of Rules

Table 1 comprehensively describes the SWRL rules designated to make the KB with reasoning capabilities, thereby imbuing AI systems, particularly CAs, with increased intelligence. These rules are instrumental in enabling AI systems to provide reasoned responses to queries. These rules adhere to an abstract syntax encompassing a sequence of axioms and facts. These axioms contain various types, including subclass axioms, equivalent class axioms and extension with rule axioms. The rule axioms are composed of two critical components: an antecedent (*body*) and a consequent (*head*); each may contain a set of atoms, which collectively contribute to the rule's logic and reasoning processes.

6. Evaluation, Verification, Testing and Implementation

A collaborative methodology that follows an ontological structure is utilized in this section 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 based on structural, semantic-relational, and lexical evaluations.

The authors used Neo4j, a KGs database, to store RDF 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[25] plugin. As a result of *15195* triples loaded and *15195* parsed,

[25] https://neo4j.com/labs/neosemantics/

the model is parsed, demonstrating the quality and consistency of the loaded model. This work illustrates the semi-automated behaviour of KGs.

6.1. Ontology Assessment Module

For ontology assessment, many approaches are used for measuring the quality of the constructed ontology from different perspectives [48-49]. The ontology engineer decides the best-fitting approach for the specific situation. The authors utilized the CQ-based verification approach from the previous studies because it includes some advantages: it covers different quality dimensions such as expressiveness, accuracy, understandability, cohesion, and consciousness. Easily applied, flexible, and adaptable for application in various contexts [45].

6.1.1. Competency Questions-based Verification

In this method, the applied ontology is verified against predefined criteria, represented in the form of competency intentions. This approach helps evaluate the quality dimensions, especially expressiveness, that depend on the ontology's ability to answer competency questions. In this research, the authors tested and verified by writing SPARQL queries and description logic (DL)[26] queries to answer CQs, execute the queries on the produced ontology, and then compare the outcomes with the expected results (*see table 2*).

Table 2 explains extensively expected results verified through CQs (*see section 3.3.1*). The execution of the desired results is testified and written in snap SPARQL query editor and description logics (DL) query editor in ontology editor tools, e.g., Protege. The executed results facts are fascinating because the SPARQL query contains meta-data information crucial for data exchange and integration. It is complicated in execution, but compared to the DL language, it is easy and natural to humans and relatively fast and easy to use. One of the drawbacks is DL query is not frequently used for the exchange of information within other data exchange platforms because of its lack of expressiveness to model all the possible semantics of business vocabularies, which will be modelled using Horn rules expressed in SWRL formalism [50].

SWRL is considered an extension of OWL made by the combination of RuleML and OWL, grounded in a first-order language (FOL), and with more expressive power than DL [50]. According to the *Closed World Assumption* (CWA), Pellet [51] provides limited support for using epistemic operators, allowing querying a KB [50]. Some prototypal applications handling OWL+SWRL are being developed, like *Hoolet*, and ontology editors like *Protege* can bridge DL reasoners and FOL theorems. A DL knowledge base is divided traditionally into two main categories: the terminology or schema, i.e. a vocabulary of the application domain called a TBox, and assertions, which are named individuals expressed in terms of the vocabulary, called the *ABox*, so *TBox* and *ABox* elements are expressed handsomely in a description language and represent two separate meta-levels in the application of specific domain especially in healthcare context [50].

DL is considered the underlying logic for business production rules and its manufacturing to adopt a well-known semantic web-style description language called OWL as our standard metadata language for business production rules. OWL-DL is used to take advantage of DL decision procedures and reasoning systems [50]. In the context of the underlying SHOIN(D) Description Logic (DL), the process of inference is complete, meaning that when using an OWL DL system, it guarantees the computation of all logical entailments and decidable, ensuring that all computations will conclude within a finite amount of time [52]. Authors can leverage a range of inference services [50], which offer several advantages in handling these logical deductions:

- ***Consistency Checking*** ensures that an ontology does not contain contradictory facts. In DL jargon, this is the operation of checking the consistency of an ABox with respect to a TBox.
- ***Concept Satisfiability*** is a validation process determining whether a class can have any instances. In cases where a class is deemed unsatisfiable, attempting to define an instance of that class would render the entire class hierarchy inconsistent. This assessment is crucial for maintaining the integrity and coherence of the class structure.
- ***Classification*** is a computational process determining the subclass relationships among all named classes, thereby generating a comprehensive class hierarchy. This class hierarchy serves as a valuable resource for

[26] https://wiki.app.uib.no/info216/images/e/ef/NardiBrachman-IntroductionToDescriptionLogic.pdf

addressing queries, including retrieving all subclasses or solely the immediate subclasses of a specific class.

- ***Realization*** is a process that identifies the most specific classes to which an individual belongs, essentially computing the direct types for each individual. This realization step typically occurs following classification because direct types are determined concerning a class hierarchy. Leveraging the classification hierarchy, retrieving all types associated with a particular individual becomes feasible..

These specific algorithms are implemented in various software tools known as reasoners. Some available reasoners include RacerPro [53], FaCT [54] and Pallet [51]. Other tools such as Drools, EasyRule[27], Rulebook[28], and OpenL Tablets[29] are being tested for business applications.

In this section, Table 3 explains production rules derived from meta-requirements outlined in the case study (*see section 3.1*). These rules have also been informed by direct observations conducted at Karolinska Hospital, Sweden, and further insights have been drawn from the pertinent literature [35]. The authors have effectively demonstrated these business production rules using SWRL and have successfully executed them within the Protege environment, as visualized in Fig. 9.

6.1.2. Using Cypher Query Structure in Neo4J

Cypher Query[30] language is used within the Neo4J environment and is the designated language for accessing data represented in the property graph. It exhibits slight differences compared to the SPARQL[31] query language used for accessing the data from web repositories structured in the resource description framework (RDF) format. Both Cypher and SPARQL draw inspiration from the structured query language (SQL)[32] in terms of their query structures. The structure of the cypher query can be seen in Table 4, adhering to the rules outlined in Table 3.

Table 4. explains production rules and their demonstration. The production rule1 is written in the cypher language, and query executed results can be seen in the Neo4j knowledge graph database for data visualization. Similarly, authors testified and executed different production rules from Table 3 in the Neo4j environment to claim that imported data (*OWL+SWRL*) is transformed into knowledge. This knowledge can be used to develop autonomous conversational agents (CAs) for enhancing the efficiency of applications within the healthcare contexts. For example, CA and its interaction behaviour in reality with other concepts in the graph database. This KG structure qualifies, according to production rule 4 in Table 3, 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.

6.2. Implementation Framework and Prototype

In this research, the authors have introduced a proof of concept for reasoning systems utilizing a knowledge graph approach. The initial prototype is a web-based application comprising several distinct components: views, models, and controls.

Views are integral elements on all web pages, serving as graphical interfaces facilitating user navigation. Models are implemented using the programming API associated with the entities within the datasets. In essence, each ontology class is linked to a corresponding programming class, such as a Python class. The control components play a vital role in implementing various features and functionalities, including:

- *Retrieve the ontology and the reasoner (the set of the SWRL rules)*
- *Construct an ontology for targeting question and answering session and collect the data from patients upon arrival in ED.*
- *Feeding the reasoner with the instance from the data set of the patient to deduce new facts.*
- *Show result consistency in alerts.*

6.2.1. Prototype Views

In this proposed web-based prototype, the author presented proof of the statement that conversational agents (CAs) make interaction sessions with the patient upon arrival at the ED and ask some relevant questions to analyze the urgency and medical assistance needed and informed the healthcare

[27] https://github.com/j-easy/easy-rules
[28] https://github.com/deliveredtechnologies/rulebook
[29] https://openl-tablets.org/
[30] https://neo4j.com/developer/cypher/guide-cypher-basics/
[31] https://www.w3.org/TR/rdf-sparql-query/
[32] https://www.w3schools.com/sql/

professionals (HPs) for further necessary actions. This assistive technological framework helps to improve the information provision (IP) and information flow procedures within the emergency units at the hospital. This solution helps two folds: first, it effectively facilitates the patient's inquiries about healthcare-related services. Second, this type of solution relieves the HPs from adopting as a coworker to improve information workflow procedures efficiently.

Fig. 10. provides the platform access with security checks and login authentication with a social security number or email address to the patient where they access healthcare initial services upon arrival at ED units.

Furthermore, CAs are dedicated to collecting patient data within interaction sessions. Fig. 11. provides the view for establishing interactive sessions with patients and their relatives. This activity aims to collect the relevant information from the patient for primary assessment during the stay in the emergency area. Suppose CAs perform an assessment and find it more critical. In that case, it generates an alarming signal to the Triage, and the dedicated team is ready to take the patient from the queue area to the emergency room for instant medical assistance. This interaction session is based on patient-related questions regarding diseases, symptoms and the nature of the acute or chronic disease. It also helps to collect quick patient-related data, which is a repetitive task for the healthcare professionals (HPs). This interactive session also provides liberty to the patient. They can express their pains or describe their current illness status. The following Fig. 11. illustrates the interactive session phenomenon.

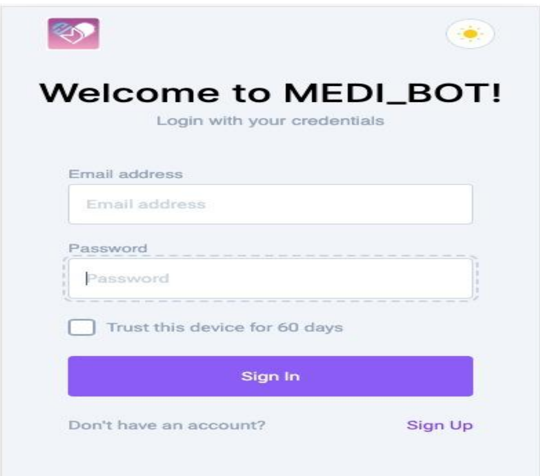


Fig. 10. Login Authentication View

Fig. 12. depicts the graphical representation of the knowledge extracted from the case study and direct observations and is grained with production rules. These rules help assess reasoners' reasoning capabilities according to the information retrieved from the ontology OWL model. The reasoners deduce new facts, recommend according to the perceived information from the ontological-based knowledge base, suggest possible medicines, and recommend medical tests according to the set rules embedded in the ontology model and stored in the knowledge graph (KG).

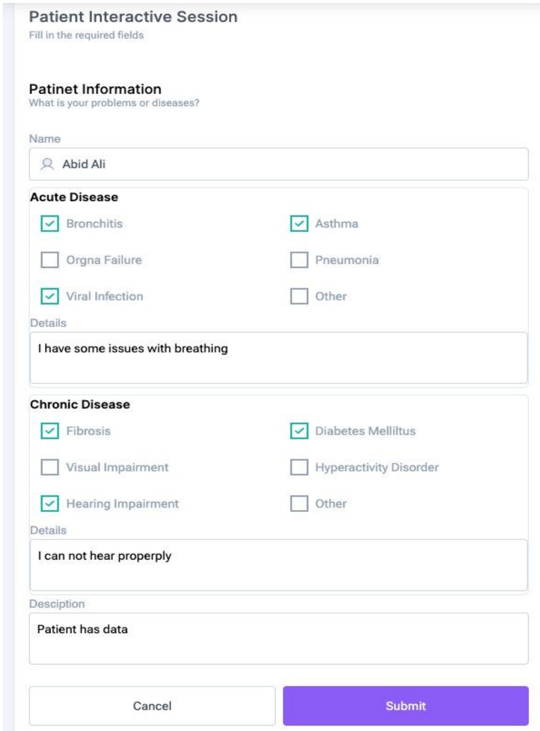


Fig. 11. Patient Interactive Session View

Success Scenario: A person "X" who interacts with the CAs and CAs asks questions and make dialogue related to the patient current illness. If the person "X" has acute disease (*e.g., bronchitis and viral infection*) and symptoms are I have some issues with breathing or person "X" has chronic disease (e.g., Fibrosis and hearing impairment) and symptoms are I can not hear properly. The CAs can suggest some medical test (*e.g., Latent Tuberculosis LTBI or Ultrasound and Hepatitis C Virus or ECGS*) and recommend medicine (*e.g., Adenosine or Olanzapine*) to healthcare professionals (HPs) according the rules which are embedded in the OWL model and feed to the reasoners.

Medi_bot: "*What is your problem or disease*"
Patient: "I have some issues with breathing"

Medi_bot: "*What type of diseases you have* "
Medi_bot: "*Do you have acute disease?*"

Patient: "I have acute disease for instance, Bronchitis and viral infections"

Medi_bot: "*Do you have chronic disease?* "

Patient: "I have chronic disease for instance, Fibrosis and hearing impairment and I am not hearing properly"

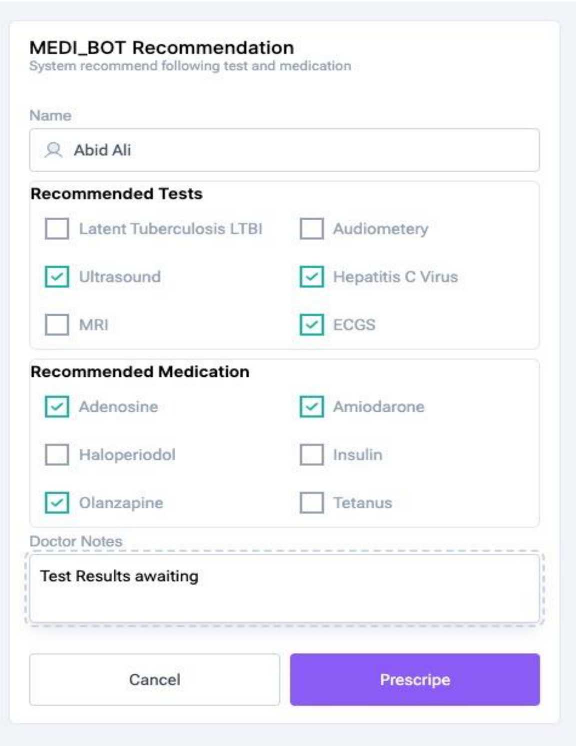


Fig. 12. Patient related Test Recommendations and Medicine recommendations based on SWRL View

6.3. Modelling Workshops

The authors presented the holistic view of the model design to domain exerts during the modelling workshops. It helps us illustrate how the domain (*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. The authors also exemplified the domain metadata 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. The authors 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.

7. Discussion

The significance of this research is to assess the feasibility of an knowledge graph-driven framework that supports CAs, and efficacy of the CAs and their usage in collaborative environments, especially in the healthcare sector, especially in ED and how these new technologies, such as CAs, help to improve patient information flows procedures and information provision (IP) and facilitate healthcare professionals in peak hours within EDs. This research targeted questions narrated in section 1. The research focuses on developing autonomous social robots, such as CAs, to reduce users' time searching for relevant information in hospital settings and improve information flow procedures utilizing knowledge-based intelligent CAs. The experiment results mentioned in sections 5 and PEDology, are well-qualified evidence to answer the above-mentioned questions and their contributions to improving the overall workflows in the PED context. They also explored some multi-stakeholders perspectives, such as patients and experiences, and perceived benefits of including CAs in their premises, especially in the ED environment. This section also discussed some risks and challenges associated with CAs in the healthcare domain.

The perceived benefits to end-users are the leading indicators to measure the efficacy of CAs' inclusion in the healthcare sector. Simultaneously, the HPs and domain experts are keen to have CAs in ED premises to achieve some goals to improve patient workflow procedures. These innovative technological solutions can serve as mediating agents to facilitate HPs during peak hours in EDs. These perceived benefits are classified: a straightforward approach to healthcare providers, helping patients with their better personalized health management, preventing unnecessary visits to the healthcare provider to avoid overcrowding situations, facilitating patients with quality care upon arrival and helping to reduce their stress levels in waiting areas and provide freedom to share their sensitive information to CAs compared to healthcare provider not facing a bullying situation and feel embarrassment, and also helps in patient's privacy effectively. According to published facts and statistics, an average of *65%* (*SD=13.24*) agreed to some extent that there are benefits associated with health CAs, and an average of *17%* (*SD=6.12*) disagreed to some extent that there were any potential benefits associated with health CAs. It also facilitates HPs to perform collaborative tasks such as self-management, education, training, counselling, cognitive behaviour therapy, screening, and diagnosing [55]

7.1. Patient Perspective and Technology Acceptance

According to the patient's perspective, CAs can be facilitated patients in different applications scenarios such as self-diagnosis, anamnesis, medication counselling and dosage, prioritization in the emergency room (*i.e. that is, the core discussion*), psychiatric treatment, treatment information, food orders, and improve information flow and information provision [56]. Clear and accurate communication in a natural way is the essence associated with CAs and is valued by patients. Usually, patients restrained in the hospital during an ED visit mentioned a need for more understanding and better communication from HPs regarding the decision to use restraints. In ED premises, most patients and their supporters are unable to understand the medical jargon, leading to worsened mental states due to stress and loss of control [57].

7.2. Healthcare Professionals (HPs) Perspective and Technology Acceptance

According to the HPs' perspective, CAs can be helpful as an automated tool in different application scenarios, including quality diagnosis as an aid to improve decision-making, helping in the interpretation of clinical images like computer tomography images and X-ray images, information about a patient, e.g. medical history of the patient in terms of recent diseases and allergies for physicians and captures the progression of the disease regularly in EDs. They also support information about a patient in the operation room, like medical history or last blood samples from the patient before physicians start surgery. CAs serve as an interactive knowledge base where end-users can ask relevant queries, such as currently discovered diseases and new treatment methods. CAs can be used to support the documentation work of physicians. For many physicians, the documentary obligation seems to be a burden, which takes much time in the daily life of a physician. CAs also support communication between different healthcare facilities, If a physician needs specific information about recent patient treatments by a different facility [56]. According to the observations in EDs, most HPs described difficulty communicating with frequent patients of the ED with multiple disorders and diseases, and they had trouble addressing the primary concern when patients presented with numerous associated pathologies and symptoms. So, they look forward to incorporating a mediating tool which works as a co-worker alliance for creating coworking value creations in the peak hours of EDs [57].

7.3. Perceived Challenges and Risks Associated with Conversational Agents (CAs)

Along with the benefits of using CAs, some challenges and risks are involved. According to the facts conducted by [55], *54%*, an average of more than half of the respondents, agreed that there are various challenges and risks with using CAs for patients. The CAs are unable to mitigate adequately understand or display human emotions approximately *86%*, unable to full patient needs approximately *77%*, lacking in intelligence or knowledge to access patients approximately *73%* accurately, and patient data privacy and confidentiality approximately *59%* as perceived challenges and risks [55]. Similarly, some domain-specific constraints are also critical in terms of anticipated regret of CAs' mistakes and errors with wrong suggestions because of malfunctions or wrong inputs of the users and privacy concerns because of sensitive patient data [56].

8. Conclusion and Future Work

This research focuses on the utilization of knowledge graphs (KGs) as a framework that can be used for training and advancing conversational applications. The primary goal is to assist and facilitate healthcare professionals (HPs) as coworkers and help for seamless interactions between patients and machines, AI systems, enabling on-demand access to health-related services. To achieve this, the authors adopted a rigorous and iterative approach known as CRISP-KG methodology. Our objective was to develop KGs that capture the contextual domain knowledge of the domain and assess novel ontological model artifacts. In the process, the authors employed a well-recognized collaborative methodology (CM) to design and implement the domain ontology specific to the *Pediatric Emergency Department* (PED), referred to as (PEDology).

This proposed work presents an advanced knowledge graph (KG) approach, semi-automated for developing intelligent conversational agents (CAs). These CAs serve as intermediaries between patients and healthcare providers, facilitating practical and beneficial interactions before and after arrival at medical facilities. The primary aim is to address and alleviate overcrowding issues within healthcare departments.

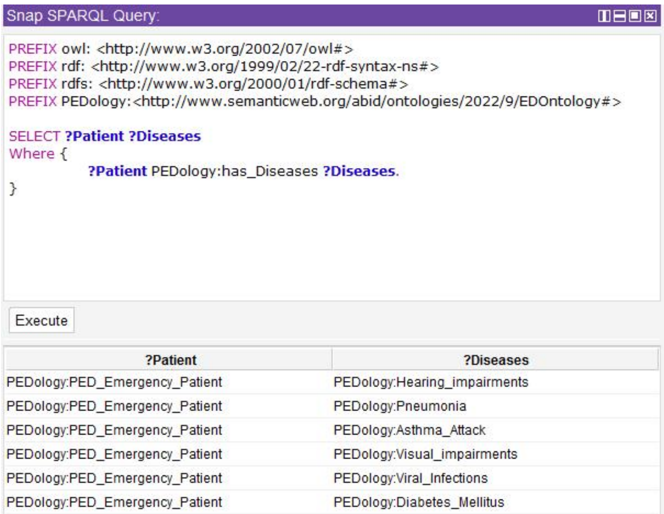
By harnessing the power of knowledge graphs, this approach offers a more effective means of creating new types of Information Systems (ISs) in the healthcare domain. It achieves this by constructing models that accurately represent specific healthcare units, thus enabling the design and deployment of intelligent solutions. This KG-based approach is instrumental in automating various tasks and processes within healthcare organizations, improving efficiency and effectiveness in healthcare services.

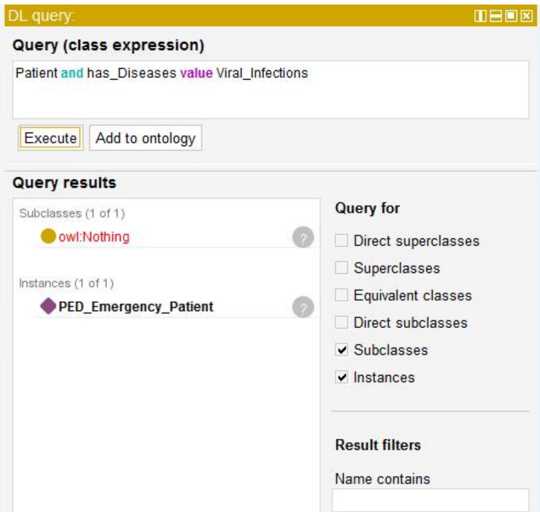
For futuristic studies, the authors emphasize how CAs can benefit the resident's educational training, especially in emergencies, and how CAs promise to enhance patients' health promotion and rehabilitation process in emergencies.

Acknowledgement: The authors would like to thank the *Karolinska Institutet* (KI) administration for their invaluable collaboration throughout the visit, their enthusiastic engagement during the modelling workshop at *Karolinska Hospital*, *Solna, Stockholm, Sweden* and their unwavering support throughout the course.

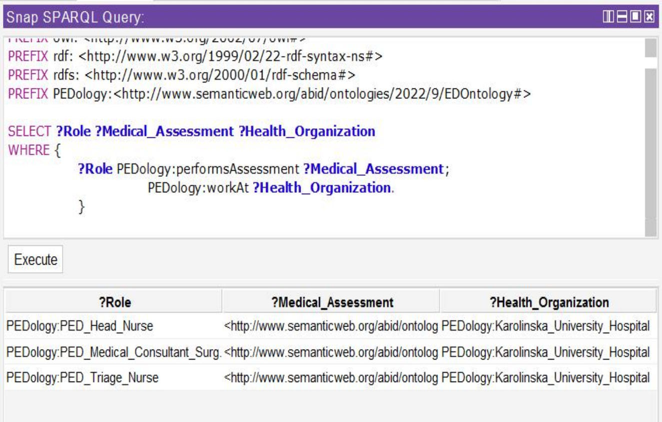
Table. 2. Expected results verified through competency questions.

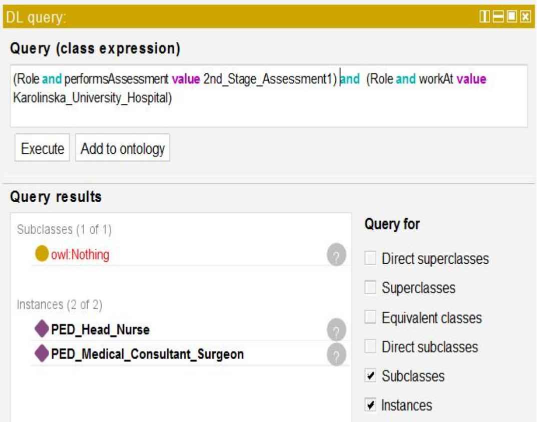
CQ1: What patient have specific diseases?



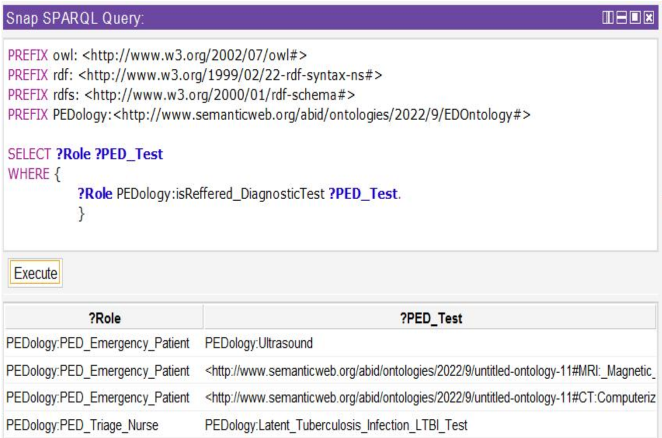


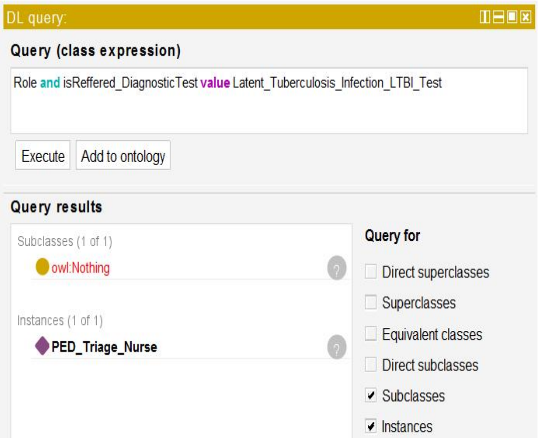
CQ2: Who is responsible for performing medical assessment in emergency department?



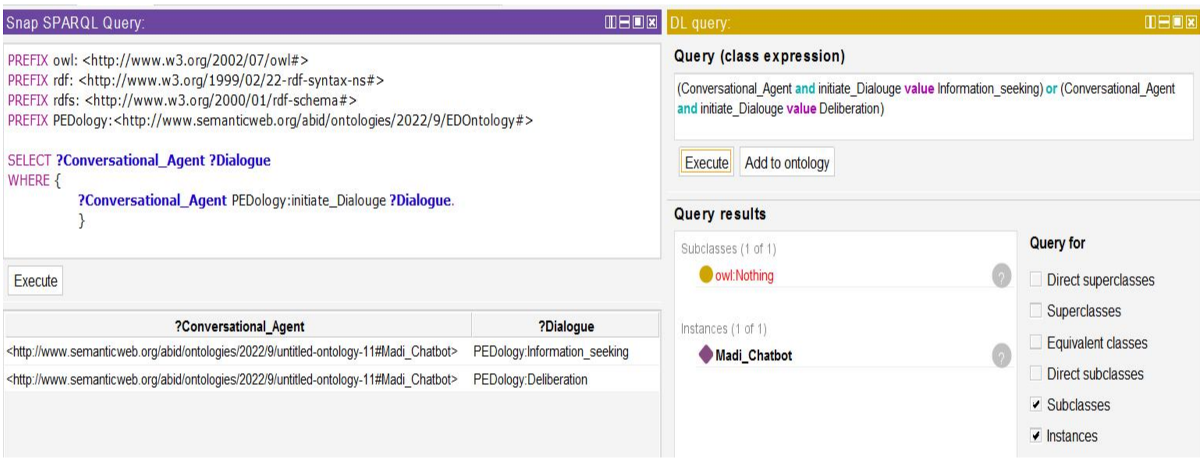


CQ3: What roles are referred for diagnostic test during assessment in emergency department?

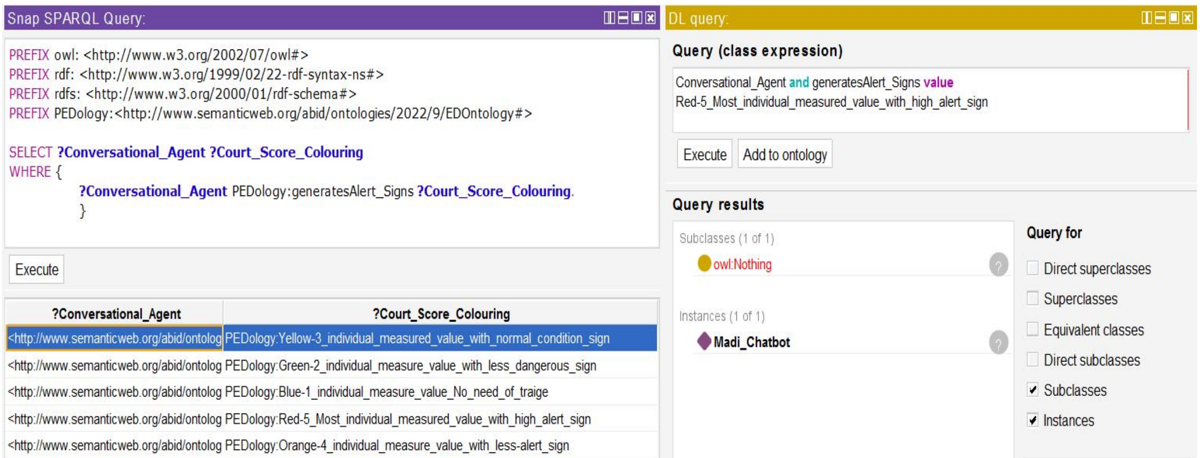




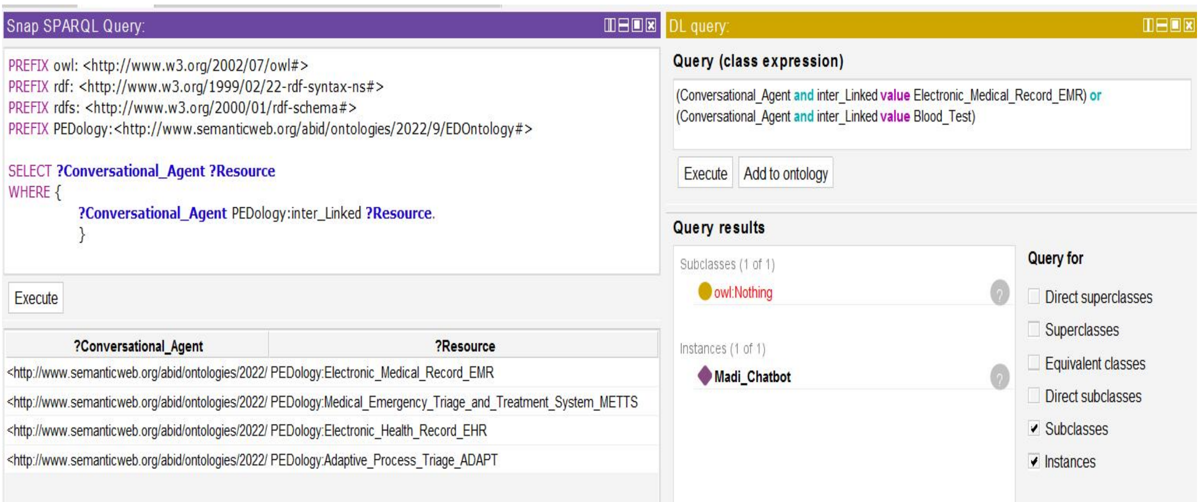
CQ4: How conversational agent initiate dialogues in emergency unit?



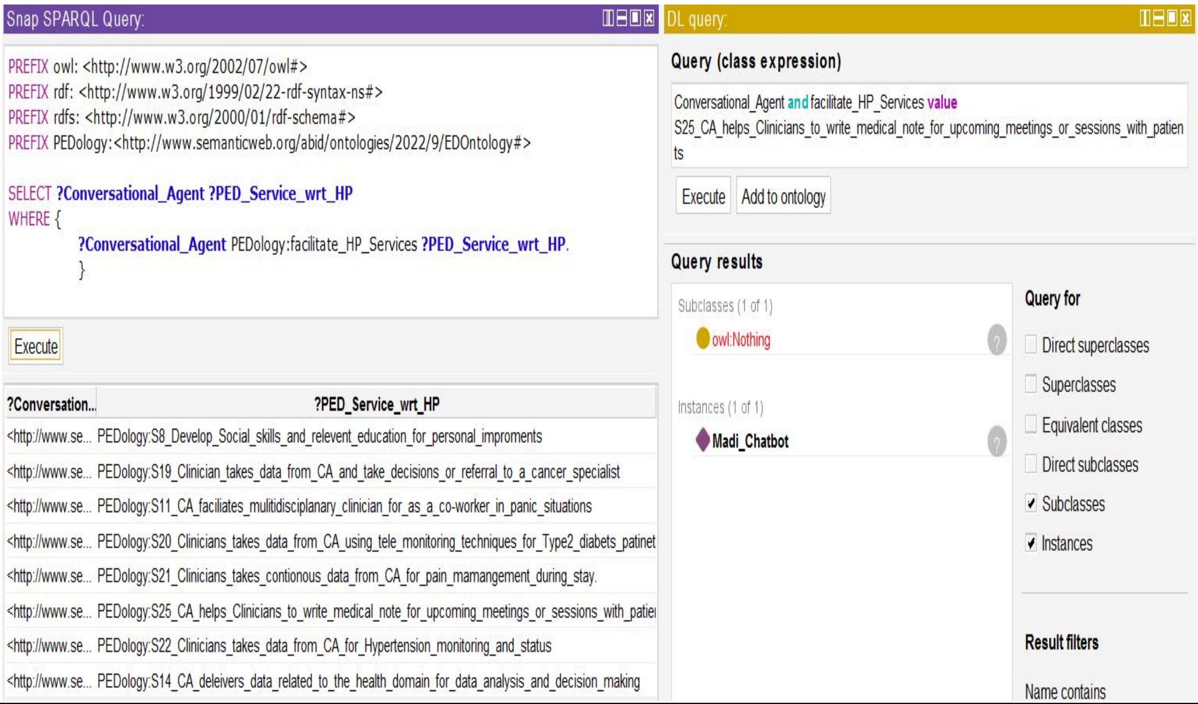
CQ5: How conversational agent generate alert signal during assessment in case emergency?



CQ6: How conversational agent interlinked with other resources?



CQ7: What type of the services offered by conversational agent to healthcare professionals within emergency unit?



CQ8: What type of the services offered by conversational agent to patients within emergency unit?

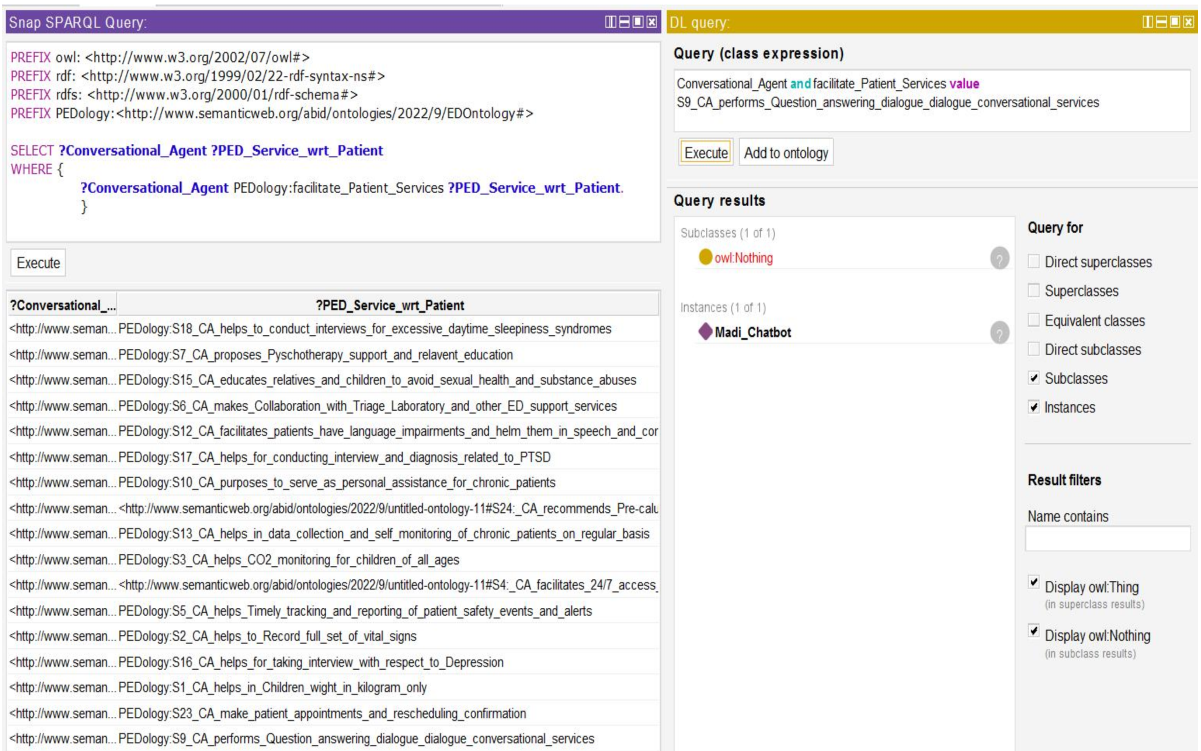


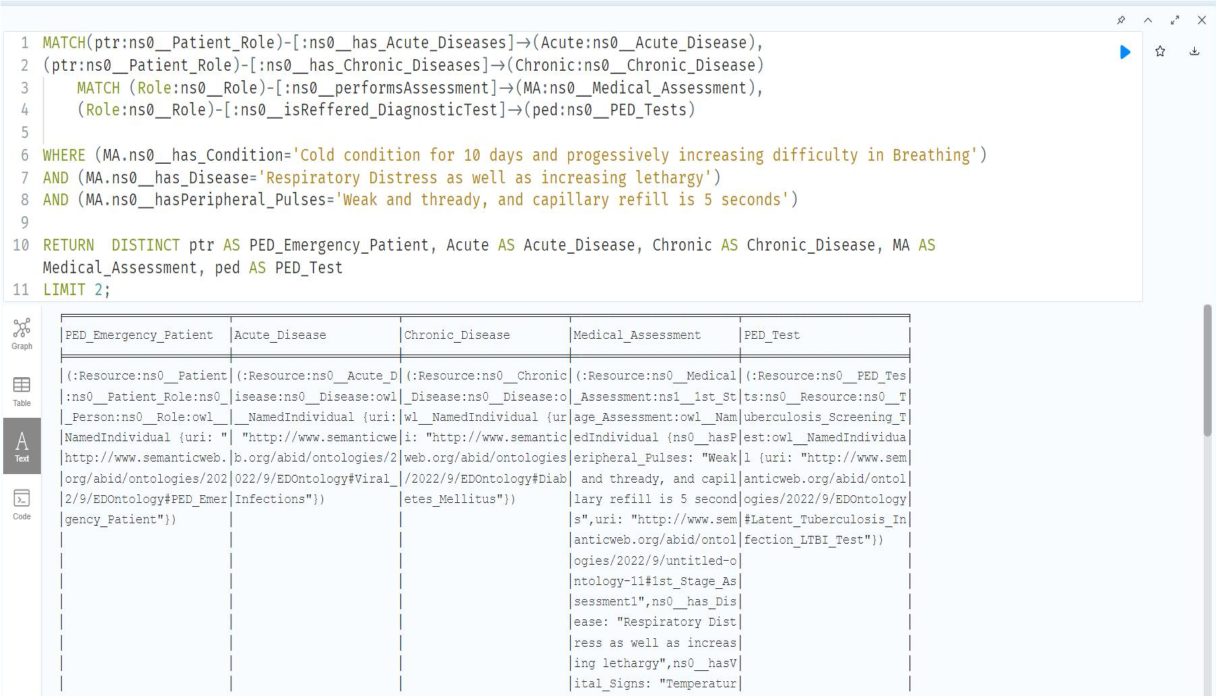
Table 3: Context-aware SWRL- Production Rule Embodied in the OWL Meta Models related to ED

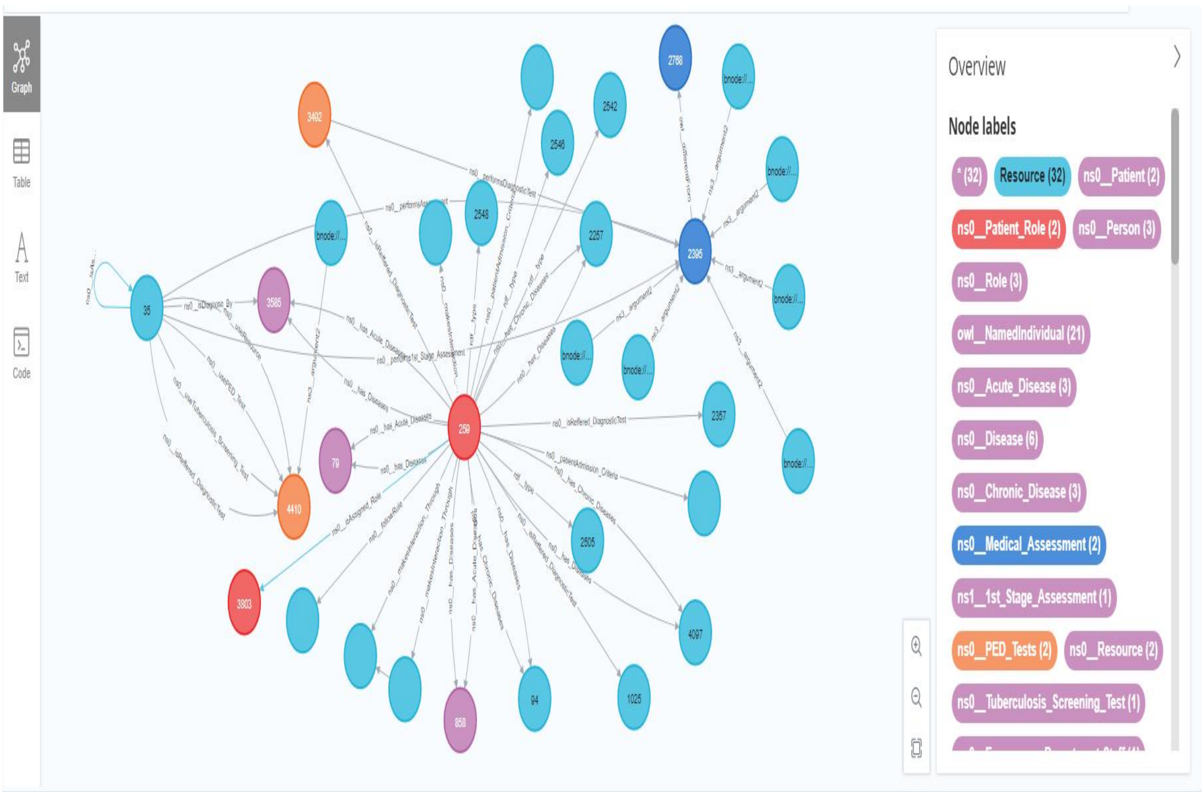
	SWRL-Rules / Production Rules
1	Patient_Role(?p)∧has_Disease(?p,"Asthma_Attack") ∧has_Disease(?p, Viral_Infections") ∧Role (?R)∧ performsAssessment (?R, 1st_Stage_Assessment1) → isReffered_Di-agnosticTest (?R, Latent_Tuberculosis_Infection_LTBI_Test)
2	Patient_Role(?p) ∧has_Disease (?p,"Hearing_impairment")∧Role (?R)∧performsAssessment (?R,1st_Stage_Assessment1) → isReffered_DiagnosticTest (?p, Audiome-tery_Test)
3	Patient_Role (?p) ∧ has_Disease (?p, "Diabetes_Mellitus") ∧Role (?R)∧performsAssessment (?R, 1st_Stage_Assessment1) → isReffered_DiagnosticTest (?p, Cholesterol_Screening_Test)
4	Person (?p) ∧hasCultural_Competence (?p,Language_Competence_Strong_Level)∧has- General_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)
5	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)
6	Conversational_Agent (?CA) ∧ initiate_Dialouge (?CA, Deliberation) ∧ initiate_Dialouge (?CA, Information_seeking)∧ enhancePersonalized_Learning_By (?CA, PED_Triage_Nurse) → actLike_Expert_System (?CA, PED_Medical_School_Graduate_in_Training)
7	Person(?p) ∧ hasCultural_Competence (?p, Language_Competence-Strong_Level) ∧ hasGeneral_Competence (?p, Ability_to_Handle_Situation_Excellent_Level) ∧ hasOccupational_Competence (?p, PED_Nursing) ∧hasWork_Experience_Competence (?p, 3-5_Years) → isAssigned_Role(PED_Triage_Nurse, ?p)
8	Conversational_Agent(?CA) ∧ recommend_Medicine(?CA, Antipsychotics) ∧ facilitate_Patient_Services (?CA, S15_CA_educates_relatives_and children_to_avoid_sexual_health_and_substance_abuses)∧ facilitate_HP_Services (?CA, S20_CA_ using_tele_monitoring_techniques_for_Type2_ diabetes_ patients) → Expert_System (?CA, Physical_Health_Violence_Monitoring_Status1)

Fig. 10. PED SWRL Production rules

Table 4. PEDology related prodcution rules and their execution in Neo4j using cypher queries.

Production Rule1: Patient_Role (?p)∧has_Disease (?p,"Asthma_Attack") ∧has_Disease (?p, "Viral_Infections") ∧Role (?R) ∧performsAssessment (?R, "1st_Stage_Assessment1") → isReffered_Di-agnosticTest (?R, "Latent_Tuberculosis_Infection_LTBI_Test")

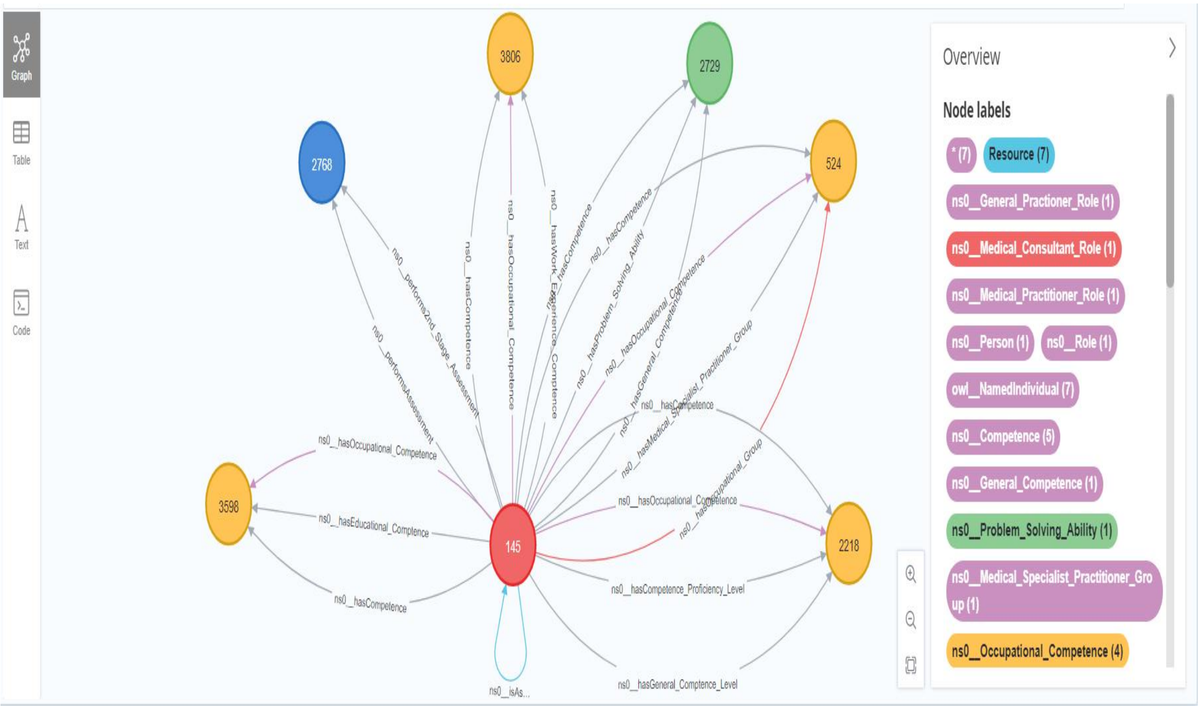

MATCH(ptr:ns0__Patient_Role)-[:ns0__has_Acute_Diseases]→(Acute:ns0__Acute_Disease),
(ptr:ns0__Patient_Role)-[:ns0__has_Chronic_Diseases]→(Chronic:ns0__Chronic_Disease)
MATCH (Role:ns0__Role)-[:ns0__performsAssessment]→(MA:ns0__Medical_Assessment),
(Role:ns0__Role)-[:ns0__isReffered_DiagnosticTest]→(ped:ns0__PED_Tests)
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;
Graph
Table
Text
Code
PED_Emergency_Patient
Acute_Disease
Chronic_Disease
Medical_Assessment
PED_Test
(:Resource:ns0__Patient:ns0__Patient_Role:ns0__Person:ns0__Role:owl__NamedIndividual {uri: "http://www.semanticweb.org/abid/ontologies/2022/9/EDOntology#PED_Emergency_Patient"})
(:Resource:ns0__Acute_Disease:ns0__Disease:owl__NamedIndividual {uri: "http://www.semanticweb.org/abid/ontologies/2022/9/EDOntology#Viral_Infections"})
(:Resource:ns0__Chronic_Disease:ns0__Disease:owl__NamedIndividual {uri: "http://www.semanticweb.org/abid/ontologies/2022/9/EDOntology#Diabetes_Mellitus"})
(:Resource:ns0__Medical_Assessment:ns1__1st_Stage_Assessment:owl__NamedIndividual {ns0__hasPeripheral_Pulses: "Weak and thready, and capillary refill is 5 seconds",uri: "http://www.semanticweb.org/abid/ontologies/2022/9/untitled-ontology-11#1st_Stage_Assessment1",ns0__has_Disease: "Respiratory Distress as well as increasing lethargy",ns0__hasVital_Signs: "Temperatur
(:Resource:ns0__PED_Tests:ns0__Resource:ns0__Tuberculosis_Screening_Test:owl__NamedIndividual {uri: "http://www.semanticweb.org/abid/ontologies/2022/9/EDOntology#Latent_Tuberculosis_Infection_LTBI_Test"})


Graph
Table
Text
Code
Overview
Node labels
* (32)
Resource (32)
ns0__Patient (2)
ns0__Patient_Role (2)
ns0__Person (3)
ns0__Role (3)
owl__NamedIndividual (21)
ns0__Acute_Disease (3)
ns0__Disease (6)
ns0__Chronic_Disease (3)
ns0__Medical_Assessment (2)
ns1__1st_Stage_Assessment (1)
ns0__PED_Tests (2)
ns0__Resource (2)
ns0__Tuberculosis_Screening_Test (1)

Prodcution Rule2: Person(?p)∧hasCultural_Competence(?p, Language_Competence_Strong_Level)∧has-General_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)

```
MATCH
    (ptr:ns0__Person)-[:ns0__hasCultural_Competence]→(cl:ns0__Cultural_Competence),
    (ptr:ns0__Person)-[:ns0__hasGeneral_Competence]→(gc:ns0__General_Competence),
    (ptr:ns0__Person)-[:ns0__hasOccupational_Competence]→(oc:ns0__Occupational_Competence),
    (ptr:ns0__Person)-[:ns0__hasWork_Experience_Comptence]→(wc:ns0__Work_Experience_Comptence),
    (ptr:ns0__Person)-[:ns0__performs2nd_Stage_Assessment]→(MA:ns0__Medical_Assessment),
    (ptr:ns0__Person)-[:ns0__hasEducational_Comptence]→(ec:ns0__Educational_Competence),
    (ptr:ns0__Person)-[:ns0__isAssigned_Role]→(tnr:ns0__Medical_Consultant_Role)
WHERE (tnr.ns0__has_Age=50)
RETURN DISTINCT ptr AS Person, gc AS General_Competence, oc AS Occupational_Competence, wc AS Work_Experience, MA AS
Medical_Assessment, ec AS Educational_Merit, tnr AS Role_Name
LIMIT 2;
```

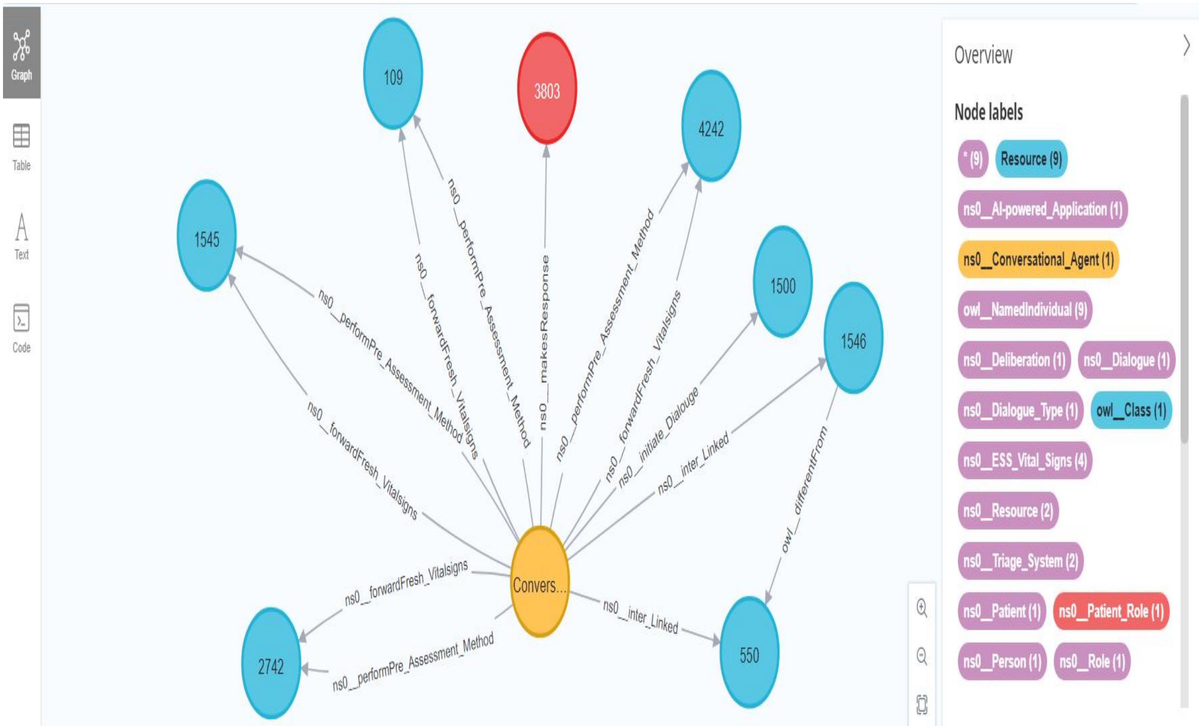
Person	General_Competence	Occupational_Competence	Work_Experience	Medical_Assessment	Educational_Merit	Role_Name
(:Resource:ns0__General_Practioner_Role:ns0__Medical_Consultant_Role:ns0__Medical_Practitioner_Role:ns0__Person:ns0__Role:owl__NamedIndividual {ns0__has_Age: 50,uri: "http://www.semanticweb.org/abid/ontologies/2022/9/EDOntology#PED_Medical_Consultant_Surgeon"})	(:Resource:ns0__Competence:ns0__General_Competence:ns0__Problem_Solving_Ability:owl__NamedIndividual {uri: "http://www.semanticweb.org/abid/ontologies/2022/9/EDOntology#Problem_Solving_Ability_Strong_Level"})	(:Resource:ns0__Competence:ns0__Medical_Specialist_Practitioner_Group:ns0__Occupational_Competence:ns0__Occupational_Group:owl__NamedIndividual {uri: "http://www.semanticweb.org/abid/ontologies/2022/9/EDOntology#Medical_Specialist_Practitioner_Group1"})	(:Resource:ns0__Competence:ns0__Occupational_Competence:ns0__Work_Experience_Comptence:owl__NamedIndividual {uri: "http://www.semanticweb.org/abid/ontologies/2022/9/untitled-ontology-11#8-10_Years"})	(:Resource:ns0__Medical_Assessment:ns1__2nd_Stage_Assessment:owl__NamedIndividual {ns0__makeDecision: "Make decsion for the furtehr medical diagnostic procedures, observations, treatment plans according to the guidlne or Rehabilitation process",uri: "http://www.semanticweb.org/abid/ontologies/2022/9/untitled-ontol	(:Resource:ns0__Competence:ns0__Educational_Competence:ns0__Occupational_Competence:owl__NamedIndividual {uri: "http://www.semanticweb.org/abid/ontologies/2022/9/EDOntology#MBBS_MBchB_BMed_Dr.med_Ph.d"})	(:Resource:owl__NamedIndividual:ns0__Person:ns0__General_Practioner_Role:ns0__Medical_Consultant_Role:ns0__Role:ns0__Medical_Practitioner_Role {ns0__has_Age: 50,uri: "http://www.semanticweb.org/abid/ontologies/2022/9/EDOntology#PED_Medical_Consultant_Surgeon"})



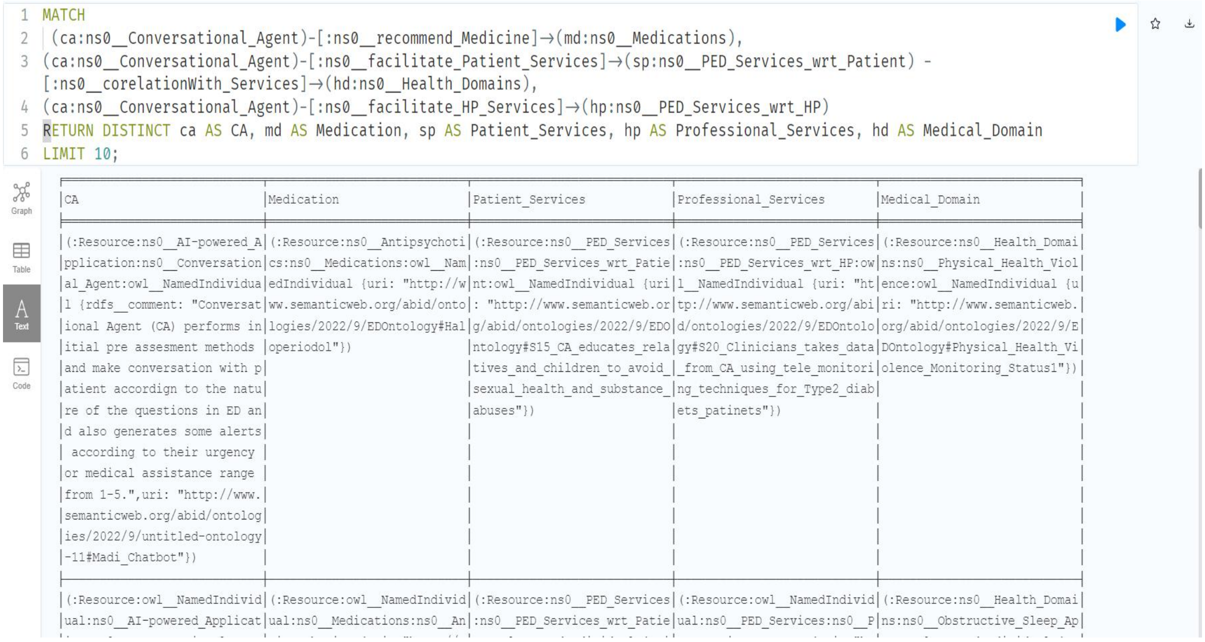
Production Rule3: Conversational_Agent(?CA)∧initiate_Dialouge(?CA, Deliberation)∧initiate_Dialouge(?CA, Information_seeking)∧forwardFresh_Vitalsigns(?CA, RLS)∧forwardFresh_Vitalsigns(?CA, Body_Temperature_Method)∧inter_Linked(?CA, Adaptive_Process_Triage_ADAPT) → makesResponse(?CA, PED_Malin_Braun)

```
MATCH(ca:ns0__Conversational_Agent)-[:ns0__initiate_Dialouge]→(dt:ns0__Dialogue_Type),
(ca:ns0__Conversational_Agent)-[:ns0__forwardFresh_Vitalsigns]→(ess:ns0__ESS_Vital_Signs),
(ca:ns0__Conversational_Agent)-[:ns0__inter_Linked]→(ts:ns0__Triage_System),
(ca:ns0__Conversational_Agent)-[:ns0__makesResponse]→(pr:ns0__Patient_Role)
RETURN ca AS Consational_Agent, dt AS Dialogue_Type,ess AS Vital_signs,ts AS Triage_Systems, pr AS Patient_Role
LIMIT 5;
```

```
|Consational_Agent            |Dialogue_Type                |Vital_signs                  |Triage_Systems               |Patient_Role                 |
|(:Resource:ns0__AI-powered_Ap|(:Resource:ns0__Deliberation:|(:Resource:ns0__ESS_Vital_Sig|(:Resource:ns0__Resource:ns0_|(:Resource:ns0__Patient:ns0__|
|plication:ns0__Conversational|ns0__Dialogue:ns0__Dialogue_T|ns:owl__NamedIndividual {rdfs|_Triage_System:owl__NamedIndi|Patient_Role:ns0__Person:ns0_|
|_Agent:owl__NamedIndividual {|ype:owl__Class:owl__NamedIndi|__comment: "Facts:\n
Red Sign|vidual {uri: "http://www.sema|_Role:owl__NamedIndividual {n|
|rdfs__comment: "Conversationa|vidual {uri: "http://www.sema|: Not Used ---Alert
Orange Si|nticweb.org/abid/ontologies/2|s0__has_Age: 3,ns0__first_Nam|
|l Agent (CA) performs initial|nticweb.org/abid/ontologies/2|gn: Body Temperature > 41 or |022/9/EDOntology#Adaptive_Pro|e: "Malin",ns0__has_Sex: "Fem|
| pre assesment methods and ma|022/9/EDOntology#Deliberation|< 35 --- Alert
Yellow Sign: B|cess_Triage_ADAPT"})          |ale",ns0__date_and_Time: "202|
|ke conversation with patient |"})                          |ody Temperature range (38.5 -|                             |2-04-12T13:20:00-05:00",uri: |
|accordign to the nature of th|                             | 41)---Alert
Green Sign: Body|                              |"http://www.semanticweb.org/a|
|e questions in ED and also ge|                             | Temperature range (35.1 - 38|                             |bid/ontologies/2022/9/EDOntol|
|nerates some alerts according|                             |.4) ---Alert
Blue Sign: Not |                               |ogy#PED_Malin_Braun",ns0__las|
| to their urgency or medical |                             |in need of Triage",uri: "http|                             |t_Name: "Braun"})            |
|assistance range from 1-5.",u|                             |://www.semanticweb.org/abid/o|                             |                             |
|ri: "http://www.semanticweb.o|                             |ntologies/2022/9/EDOntology#B|                             |                             |
|rg/abid/ontologies/2022/9/unt|                             |ody_Temperature_Method"})    |                             |                             |
```

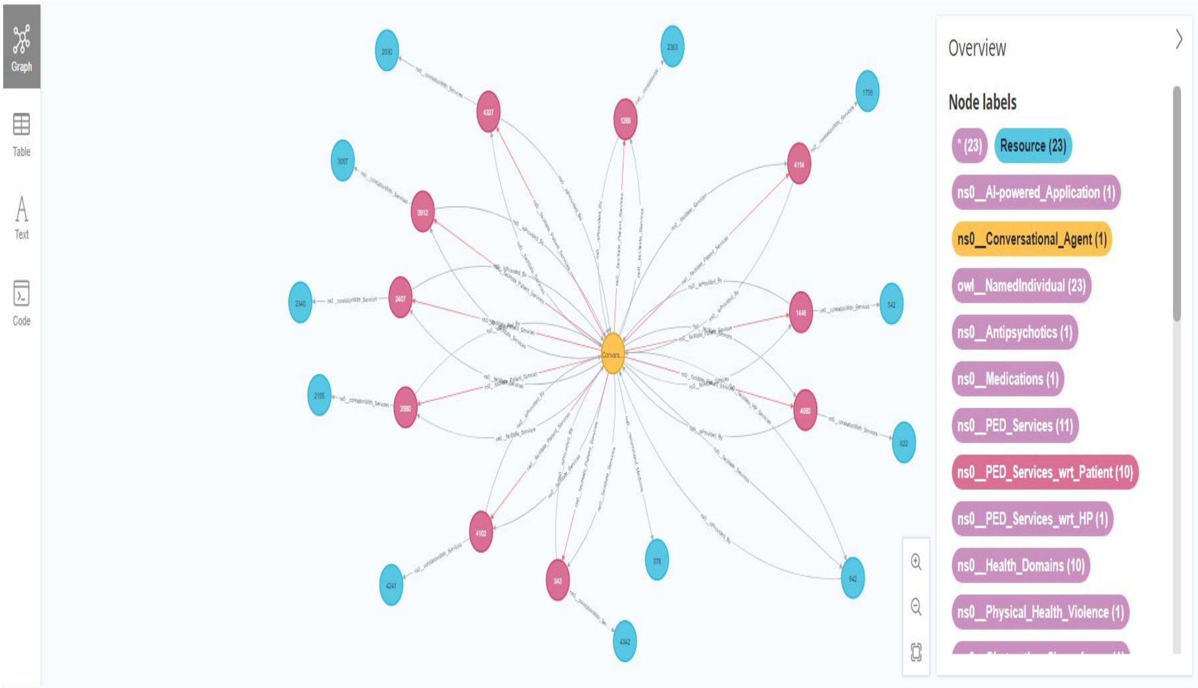


Production Rule4: Conversational_Agent(?CA) ∧ recommend_Medicine(?CA, Antipsychotics) ∧ facilitate_Patient_Services(?CA, S15_CA_educates_relatives_and children_to_avoid_sexual_health_and_substance_abuses)∧ facilitate_HP_Services(?CA, S20_CA_ using_tele_monitoring_techniques_for_Type2_ diabetes_ patients) → Expert_System(?CA, Physical_Health_Violence_Monitoring_Status1)



```
MATCH
 (ca:ns0__Conversational_Agent)-[:ns0__recommend_Medicine]→(md:ns0__Medications),
(ca:ns0__Conversational_Agent)-[:ns0__facilitate_Patient_Services]→(sp:ns0__PED_Services_wrt_Patient) -
[:ns0__corelationWith_Services]→(hd:ns0__Health_Domains),
(ca:ns0__Conversational_Agent)-[:ns0__facilitate_HP_Services]→(hp:ns0__PED_Services_wrt_HP)
RETURN DISTINCT ca AS CA, md AS Medication, sp AS Patient_Services, hp AS Professional_Services, hd AS Medical_Domain
LIMIT 10;
```

CA	Medication	Patient_Services	Professional_Services	Medical_Domain
(:Resource:ns0__AI-powered_Application:ns0__Conversational_Agent:owl__NamedIndividual {rdfs__comment: "Conversational Agent (CA) performs initial pre assesment methods and make conversation with patient accordign to the nature of the questions in ED and also generates some alerts according to their urgency or medical assistance range from 1-5.",uri: "http://www.semanticweb.org/abid/ontologies/2022/9/untitled-ontology-11#Madi_Chatbot"})	(:Resource:ns0__Antipsychotics:ns0__Medications:owl__NamedIndividual {uri: "http://www.semanticweb.org/abid/ontologies/2022/9/EDOntology#Haloperiodol"})	(:Resource:ns0__PED_Services:ns0__PED_Services_wrt_Patient:owl__NamedIndividual {uri: "http://www.semanticweb.org/abid/ontologies/2022/9/EDOntology#S15_CA_educates_relatives_and_children_to_avoid_sexual_health_and_substance_abuses"})	(:Resource:ns0__PED_Services:ns0__PED_Services_wrt_HP:owl__NamedIndividual {uri: "http://www.semanticweb.org/abid/ontologies/2022/9/EDOntology#S20_Clinicians_takes_data_from_CA_using_tele_monitoring_techniques_for_Type2_diabets_patinets"})	(:Resource:ns0__Health_Domains:ns0__Physical_Health_Violence:owl__NamedIndividual {uri: "http://www.semanticweb.org/abid/ontologies/2022/9/EDOntology#Physical_Health_Violence_Monitoring_Status1"})
(:Resource:owl__NamedIndividual:ns0__AI-powered_Applicat	(:Resource:owl__NamedIndividual:ns0__Medications:ns0__An	(:Resource:ns0__PED_Services:ns0__PED_Services_wrt_Patie	(:Resource:owl__NamedIndividual:ns0__PED_Services:ns0__P	(:Resource:ns0__Health_Domains:ns0__Obstructive_Sleep_Ap



References

[1] K. Basu, Conversational ai: Open domain question answering and commonsense reasoning, arXiv preprint arXiv:1909.08258 (2019).

[2] A. Alnefaie, S. Singh, B. Kocaballi, M. Prasad, An overview of conversational agent: applications, challenges and future directions, in: 17th International Conference on Web Information Systems and Technologies, SCITEPRESS-Science and Technology Publications, 2021.

[3] D. Kadariya, R. Venkataramanan, H. Y. Yip, M. Kalra, K. Thirunarayanan, A. Sheth, kbot: knowledge-enabled personalized chatbot for asthma self-management, in: 2019 IEEE International Conference on Smart Computing (SMARTCOMP), IEEE, 2019, pp. 138–143.

[4] S. S. Skov, J. R. Andersen, S. Lauridsen, M. Bab, M. Bundsbæk, M. B. D. Nielsen, Designing a conversational agent to promote teamwork and collaborative practices using design thinking: An explorative study on user experiences, Frontiers in Psychology 13 (2022) 903715–903715.

[5] J. Weizenbaum, Eliza—a computer program for the study of natural language communica- tion between man and machine, Communications of the ACM 9 (1966) 36–45.

[6] S. Hussain, O. Ameri Sianaki, N. Ababneh, A survey on conversational agents/chatbots classification and design techniques, in: Web, Artificial Intelligence and Network Applications: Proceedings of the Workshops of the 33rd International Conference on Advanced Information Networking and Applications (WAINA-2019) 33, Springer, 2019, pp. 946–956.

[7] B. Bayat, J. Bermejo-Alonso, J. Carbonera, T. Facchinetti, S. Fiorini, P. Goncalves, V. A. Jorge, M. Habib, A. Khamis, K. Melo, et al., Requirements for building an ontology for autonomous robots, Industrial Robot: An International Journal 43 (2016) 469–480.

[8] G. H. Lim, I. H. Suh, H. Suh, Ontology-based unified robot knowledge for service robots in indoor environments, IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans 41 (2010) 492–509.

[9] K. Munir, M. S. Anjum, The use of ontologies for effective knowledge modelling and information retrieval, Applied Computing and Informatics 14 (2018) 116–126.

[10] C. Peng, F. Xia, M. Naseriparsa, F. Osborne, Knowledge graphs: Opportunities and challenges, Artificial Intelligence Review (2023) 1–32.

[11] C. Grosan, A. Abraham, Intelligent systems, volume 17, Springer, 2011.

[12] S. Manzoor, Y. G. Rocha, S.-H. Joo, S.-H. Bae, E.-J. Kim, K.-J. Joo, T.-Y. Kuc, Ontology-based knowledge representation in robotic systems: a survey oriented toward applications, Applied Sciences 11 (2021) 4324.

[13] A. Nazir, S. Sholla, A. Bashir, An ontology based approach for context-aware security in the internet of things (iot), International Journal of Wireless and Microwave Technologies (IJWMT) 11 (2021) 28–46.

[14] A. A. Fareedi, A. Ghazawneh, M. Bergquist, Artificial Intelligence Agents and Knowledge Acquisition in Health Information System, Technical Report, EasyChair, 2022.

[15] J. Sowa, Knowledge representation–logical, philosophical, and computational founda- tions. pacific grove, ca, usa: Brooks/cole. w3c–the worldwide web consortium.(2003a). the semantic web initiative, 2000.

[16] Y. fan Zhang, L. Gou, T. shu Zhou, D. nan Lin, J. Zheng, Y. Li, and J. song Li, An ontology-based approach to patient follow-up assessment for continuous and personalized chronic disease management, J. Biomed. Inform. 72 (2017) 45–59, http://dx.doi.org/10.1016/j.jbi.2017.06.021.

[17] H.B. Elhadj, F. Sallabi, A. Henaien, L. Charri, K. Shuaib, and M. A. Thawadi, Do-Care: A dynamic ontology reasoning based healthcare monitoring system, Future Generation Computer Systems 118 (2021) 417-431.

[18] International classification of diseases, Version 10, last accessed on 25/09/2023, 2010, URL https://bioportal.bioontology.org/ontologies/ICD10/?p=summary.

[19] M. Möller, M. Sintek, R. Biedert, P. Ernst, A. Dengel, D. Sonntag, Representing the international classification of diseases version 10 in owl, in: KEOD, 2010, pp. 50–59.

[20] SNOMED CT, last accessed on 25/09/2023, 2018, URL https://bioportal. bioontology.org/ontologies/SNOMEDCT.

[21] Foundational model of anatomy, last accessed on 25/09/2023, 2018, URL https://bioportal.bioontology.org/ontologies/FMA/?p=summary.

[22] International classification for nursing practice, last accessed on 25/09/2023, 2017, URL https://bioportal.bioontology.org/ontologies/ICNP.

[23] A. Alamri, Ontology middleware for integration of IoT healthcare information systems in EHR systems, Computers 7 (4) (2018) 51.

[24] R. Studer, S. Grimm, A. Abecker, Semantic web services: concepts, technologies, and applications, Springer Science & Business Media, 2007.

[25] J. J. Solaz-Portolés, V. Sanjosé, Types of knowledge and their relations to problem solving in science: directions for practice, Sísifo. Educational Sciences Journal 6 (2008) 105–112.

[26] E. E. Ogheneovo, P. A. Nlerum, Knowledge representation in artificial intelligence and expert systems using inference rule, Int. J. Sci. Eng. Res 11 (2020) 1886–1900.

[27] M. Meraji, F. Sadoughi, M. Ahmadi, M. Kahani, Designing an ontology-based health information system: A systematic approach, Life Sci. J 10 (2013) 735–739.

[28] M. Fazel-Zarandi, M. S. Fox, An ontology for skill and competency management, in: Formal Ontology in Information Systems, IOS Press, 2012, pp. 89–102.

[29] M. Dragoni, G. Rizzo, M. A. Senese, Convology: an ontology for conversational agents in digital health, in: Web Semantics, Elsevier, 2021, pp. 7–21.

[30] G. F. Luger, Artificial intelligence: structures and strategies for complex problem solving, Pearson education, 2005.

[31] S. A. Thorat, V. Jadhav, A review on implementation issues of rule-based chatbot systems, in: Proceedings of the international conference on innovative computing & communications (ICICC), 2020.

[32] R. Soni, N. Singh, Knowledge representation in artificial intelligence using domain knowl- edge and reasoning mechanism, International Journal of Scientific Engineering and Research (2015) 2347–3878.

[33] L. Daniele, P. Dockhorn Costa, L. Ferreira Pires, Towards a rule-based approach for context-aware applications, in: Dependable and Adaptable Networks and Services: 13th Open European Summer School and IFIP TC6. 6 Workshop, EUNICE 2007, Enschede, The Netherlands, July 18-20, 2007. Proceedings 13, Springer, 2007, pp. 33–43.

[34] A. A. Fareedi, A. Ghazawneh, An ontology approach for knowledge acquisition and development of health information system (HIS), 2018.

[35] C. US-Acute, Organizational transformation at a pediatric emergency department, 2022.
[36] R. Wirth, J. Hipp, Crisp-dm: Towards a standard process model for data mining, in: Proceedings of the 4th international conference on the practical applications of knowledge discovery and data mining, volume 1, Manchester, 2000, pp. 29–39.
[37] O. Corcho, M. Fernández-López, A. Gómez-Pérez, A. López-Cima, Building legal on- tologies with methontology and webode, Law and the semantic web: legal ontologies, methodologies, legal information retrieval, and applications (2005) 142–157.
[38] D. Jones, T. Bench-Capon, P. Visser, Methodologies for ontology development (1998).
[39] S. Staab, R. Studer, H. P. Schnurr, Y. Sure, Knowledge processes and ontologies, IEEE Intelligent Systems 16 (1) (2001) 26–34.
[40] H. S. Pinto, S. Staab, C. Tempich, DILIGENT: towards a fine-grained methodology for Distributed, loosely-controlled and evolving engineering of ontologies, in: ECAI, 16, 2004, p. 393.
[41] A. Gómez-Pérez, M. C. Suárez-Figueroa, NeOn methodology for building ontology networks: A Scenario-based methodology, Demetra EOOD, 2009.
[42] D. Zeginis, A. Hasnain, N. Loutas, H. F. Deus, R. Fox, K. Tarabanis, A collaborative methodology for developing a semantic model for interlinking cancer chemoprevention linked-data sources, Semantic Web 5 (2014) 127–142.
[43] V. Presutti, E. Blomqvist, E. Daga, A. Gangemi, Pattern-based ontology design, Ontology Engineering in a Networked World (2012) 35–64.
[44] M. Grüninger, and M.S. Fox, The Role of competency questions in enterprise engineering, In Benchmarking—Theory and Practice; Springer: Boston, MA, 1995; pp. 22–31.
[45] S. Haridy, R. M. Ismail, N. Badr and M. Hashem, An ontology development methodology based on ontology-driven conceptual modelling and natural langauge processing: Tourism case study, Big Data and Cogn. Comput. 7 (101) 2023.
[46] Y. Kalfoglou, B. Hu, Issues with evaluating and using publicly available ontologies (2006).
[47] A. Gómez-Pérez, Ontology evaluation, Handbook on ontologies (2004) 251–273.
[48] A. Degbelo, A. Snapshot of ontology evaluation criteria and strategies. In Proceedings of the 13th International Conference on Semantic Systems, Amsterdam, The Netherlands, 11–14 September 2017; pp. 1–8.
[49] J. Raad, C. Cruz, A survey on ontology evaluation Methods. In Proceedings of the the 7th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management, Lisbon, Portugal, 12–14 November 2015.
[50] P. Ceravolo, C. Fugazza, M. Leida, Modeling semantics of business rules, in: Inaugural IEEE Conference on Digital Ecosystems and Technologies (IEEE DEST 2007), 2007, p. 1-6.
[51] E. Sirin, B. Parsia, B. C. Grau, A. Kalyanpur, Y. Katz, Pellet: A practical OWL-DL reasoner, Journal of Web Semantics.
[52] I. Horrocks, P. Patel-Schneider: Reducing OWL entailment to description logic satisfiability, J. of Web Semantics, 19, pp 345- 357, 2004.
[53] V. Haarslev, R. Moller, Description of the RACER system and its applications, Description Logics, 2001.
[54] I. Horrocks: FaCT and iFaCT, Description Logics, 1999 - http://citeseer.ist.psu.edu/224004.html.
[55] C., Sweeney, C., Potts, E., Ennis, R., Bond, M. D., Mulvenna, S., O'Neill, M., Malcolm, L., Kuosmanen, C., Kostenius, A., Vakaloudis, G., Mcconvey, R., Turkington, D., Hanna, H., Nieminen, A., Vartiainen, K. A., Robertson, and M. F., Mctear, Can Chatbot Help Support a Person's Mental Health? Perceptions and Views from Mental Healthcare Professionals and Experts," ACM Transactions on Computing for Healthcare 2(3), pp. 1-15.
[56] L., Reis, C., Maier, J., Mattke, and T., Weitzel, "ChatBots in Healthcare: Status Quo, Application Scenarios for Physicians and Patients and Future Directions," in Proceedings of Twenty-Eight European Conference on Information Systems (ECIS2020), 2020, pp. 1-16.
[57] C., Navas, L., Wells, S. A., Bartels, M. Walker, "Patient and Provider Perspectives on Emergency Department Care Experiences among People with Mental Health Concerns," Healthcare 10(1297), 2022, pp. 1-21.