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An ontology-driven model for hospital equipment maintenance management: a case study

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Abstract
Purpose – This paper aims to establish an efficient maintenance management system tailored for healthcare facilities, recognizing the crucial role of medical equipment in providing timely and precise patient care.
Design/methodology/approach – The system is designed to function both as an information portal and a decision-support system. A knowledge-based approach is adopted centered on Semantic Web Technologies (SWTs), leveraging a customized ontology model for healthcare facilities' knowledge capitalization. Semantic Web Rule Language (SWRL) is integrated to address decision-support aspects, including equipment criticality assessment, maintenance strategies selection and contracting policies assignment. Additionally, Semantic Query-enhanced Web Rule Language (SQWRL) is incorporated to streamline the retrieval of decision-support outcomes and other useful information from the system's knowledge base. A real-life case study conducted at the University Hospital Center of Oran (Algeria) illustrates the applicability and effectiveness of the proposed approach.
Findings – Case study results reveal that 40% of processed equipment is highly critical, 40% is of medium criticality, and 20% is of negligible criticality. The system demonstrates significant efficacy in determining optimal maintenance strategies and contracting policies for the equipment, leveraging combined knowledge and data-driven inference. Overall, SWTs showcases substantial potential in addressing maintenance management challenges within healthcare facilities.
Originality/value – An innovative model for healthcare equipment maintenance management is introduced, incorporating ontology, SWRL and SQWRL, and providing efficient data integration, coordinated workflows and data-driven context-aware decisions, while maintaining optimal flexibility and cross-departmental interoperability, which gives it substantial potential for further development.

Keywords Decision-support, Healthcare, Knowledge-based system, Maintenance, Rule-based reasoning, Semantic web technologies, Domain knowledge, Knowledge inference
Paper type Research paper

1. Introduction
Maintenance plays a vital role in any field of activity. It allows to minimize interruptions and ensure an optimal equipment performance. The medical field is no exception. Indeed, its role might be even more crucial there, given that the health and safety of patients depend greatly on the equipment readiness. The last coronavirus disease 2019 (Covid-19) pandemic (2020) might be the best demonstration of this fact, as hundreds of lives were lost and thousands more became critically ill as a direct result of the unavailability of the equipment required for diagnosis and treatment (mainly testing, respiratory aid and resuscitation devices), whether due to lack or failures. In developing countries, the situation is far worse, as the inoperative devices rate reaches 50% and sometimes up to 75% of the supplied equipment in normal conditions (Khalaf,

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2004), regardless of the heavy workload associated with such pandemics and crises. This can get even more critical if the device ceases working while in use. In Egypt, for example, around 30% of medical incidents are directly related to the equipment including failures (ELMeneza and AbuShady, 2020). So, it is not a matter of equipment shortage but rather of techno-vigilance and poor maintenance management in the first place. This was also implicitly pointed out by Ribeiro *et al.* (2018), in an exploratory study conducted in Brazil, where the authors perceived a significant lack of medical device evaluation and an absence of preventive measures to avoid failures. Even in the USA, several hundred thousand medical device reports of suspected device-associated malfunctions, serious injuries and even deaths are yearly received, according to the FDA (Food and Drug Administration). These reports didn't get the deserved attention among researchers at first until Lalani *et al.* (2021) revealed in a recent study that the deadly incidents reported may be significantly higher than rated due to the perceived miscategorization and improper reporting. In fact, the underreporting of such events was pointed out earlier by Lenzer (2017) on the grounds that medical equipment is so technologically sophisticated that the more complex the device, the less likely anomalies will get detected and eventually reported. The author has gone even further by estimating the actual deaths attributable to medical devices to nearly 1.6 million, which places them among the top death causes in the USA. Regardless of the accuracy of these estimates, it should be noted that if developed countries like the USA have at least established advanced reporting systems to capture equipment-related incidents and put in place specialized agencies like the FDA to trace and inspect the associated risks and events, then most other countries including developed ones have no equivalent reliable mechanisms or organisms yet. So, on the global scale, what is hidden is likely to be worse. Even though the reported equipment-related incidents may have several root causes other than failures and malfunctions (such as misuse, manufacturing flaws, stress, assembly fault, human error, etc.), there is no doubt that regardless of the actual cause, the resulting unfortunate consequences could have been prevented or at least significantly reduced in the presence of an efficient maintenance management system that detects and addresses the anomalies beforehand through inspections, tests, replacements, recalibrations, periodic repairs, outsourcing and any other necessary action that would allow to ensure the proper functioning of medical devices and maintain optimal reliability and readiness. In this context, several studies have emerged targeting various aspects of maintenance management, such as Shamayleh *et al.* (2020), in which the authors proposed an Internet of Things (IoT)-supported predictive maintenance approach for diagnosing medical equipment failures, considering various and frequent failure modes. The same problem was addressed by Niyonambaza *et al.* (2020) through an early failure prediction long short-term memory (LSTM) neural network model for mechanical hospital equipment. On the other hand, Cardona Ortegón and Guerrero (2021) and González-Domínguez *et al.* (2021) proposed models for optimizing the frequency and policy of tomography equipment maintenance, using Markov chains, while Kamal *et al.* (2022) proposed a framework for optimizing repair and maintenance schedules in hospitals, integrating building information modeling (BIM), discrete event simulation (DES) and genetic algorithm (GA), supported with augmented reality for on-site navigation and information retrieval. However, as it can be seen through the aforementioned studies, most of the proposed work in this area focus only on the prediction and scheduling aspects, which are usually put at the center of attention in industrial maintenance, while medical equipment maintenance has some peculiarities that require considering additional aspects in their maintenance management. For a start, healthcare facilities are meant to deal with humans rather than machines; therefore, their staff has generally a very modest technical knowledge, which requires often calling-up the maintenance department even for the simplest calibration and configuration tasks that an average industrial worker can carry out by himself. Besides, most devices are within the reach of many hands (including doctors, nurses, interns, patients, visitors and cleaning staff), while only a few are qualified to handle them correctly, which increases the chances of their failure by improper use. In fact, over 50% of all technical medical equipment problems are due to operator errors (Dhillon, 2007). From another point of view, if industrial production losses caused by failures and malfunctions can be recouped after working hours or by simply having the delivery dates extended, then this is not an option in the medical field, as saving lives requires urgent and timely interventions that cannot be delayed or postponed, which makes the equipment readiness an imperative necessity at all times, particularly because there are many medical departments where the medical staff can't do much without the required equipment, such as radiology, surgery and emergency. Therefore, maintenance outsourcing is more commonly resorted to in this field compared to the industrial sector, especially since internal maintenance labor is very limited in terms of both workforce and available gear, and cannot handle the massive number of installed systems. Moreover, most of these systems are modern and implement sophisticated technologies that may require specific maintenance trainings in order to deal with them properly. These interrelated challenges constitute the main complexity in biomedical equipment management, as they imply numerous inner decisions that require the collaboration of experts from various scopes of knowledge. First, there are doctors and health professionals who assess the medical dimension of the problem as a consequence of maintenance actions. Then, there are the administrative and economical officials who deal with the logistical and financial aspects. Finally, there are, of course, the maintenance and biomedical engineers who are primarily concerned, since they handle the technical side of the problem and its reflections on the other aspects. In order to efficiently coordinate between these different parties and ensure a fruitful exchange of information and expertise, this work proposes a knowledge-based system (KBS) for healthcare equipment maintenance management.

The rest of this paper is organized as follows. The subsequent section provides a comprehensive review of relevant literature. Section 3 details the adopted research methodology alongside the proposed KBS and its components, while Section 4 is dedicated to its implementation through the Oran university hospital center (UHC) case study and the validation of its outcomes. Finally, concluding remarks are presented along with some research perspectives.

2. Literature review

Knowledge sharing is argued to be a key solution for improving organizational performance and human capital, provided that it is induced successfully (Hsu, 2008). Bimba *et al.* (2016) listed four knowledge-based modeling techniques that may help to fulfill this condition: expert systems, linguistic, ontology and cognitive, while Breuker (2013) defined three levels to represent knowledge in the model, i.e., perceptual, conceptual and semantic. Among these, the literature highlights a particular emphasis on the semantic level, particularly through Semantic Web Technologies (SWTs). The latter provide efficient instruments for formal knowledge modeling, fostering collaboration, data integration, automation, digitization and interoperability (Dunbar *et al.*, 2023). By encoding human expertise and defining shared data schemes, these not only offer instrumental modeling support but also enable improved decision-making while ensuring semantic consistency (Prasad *et al.*, 2021). SWTs are centered on ontology, which is defined by Gruber (1993) as "a specification of a representational vocabulary for a shared domain of discourse-definitions of classes, relations, functions and other objects" that allows to outline the involved action centers and decision categories along with their inter-relations, while it uses a specific language, usually OWL (Ontology Web Language) to check knowledge consistency or make implicit knowledge explicit (Bechhofer *et al.*, 2004), thus, creating a detailed and well-structured knowledge based on the problem. The gathered knowledge can then be exploited using specific rule languages, often, SWRL (Semantic Web Rule Language) and SQWRL (Semantic Query-Enhanced Web Rule Language). SWRL (Horrocks *et al.*, 2004) combines OWL-DL and OWL-Lite sublanguages of OWL with Unary/Binary Datalog RuleML (a sub-language of RuleML) to integrate rules into an OWL knowledge base, while SQWRL (O'Connor and Das, 2009) is a query language that consists of taking a standard SWRL rule antecedent and effectively treats it as a model specification.

SWTs, particularly ontologies, have proven highly effective in modeling diverse environments and providing robust decision support across diverse domains. Gupta and Gandhi (2013) outlined a systematic ontology-based approach for capturing and managing spatial shaft-position knowledge, crucial for the efficient and safe operation of steam turbines. Extending the application of ontology, Zheng *et al.* (2023) employed a knowledge-based engineering approach to customize robotic manufacturing system architectures. Ramírez-Durán *et al.* (2020) proposed an ontology supporting Industry 4.0 systems, offering a standardized vocabulary for describing extrusion machine capabilities. In the realm of Zero-Defect Manufacturing (ZDM), Alexopoulos *et al.* (2023) advocated an ontology-based approach, integrating insights from industrial IoT and Industrial Social Networking data, while Psarommatis *et al.* (2023) initiated the development and dissemination of a set of coherent reference ontologies to advance software and data interoperability, focusing on the potential of ZDM to transform manufacturing systems and their socio-technological interactions. Montero Jiménez *et al.* (2023) introduced an ontology model for Maintenance Strategy Selection and Assessment (OMSSA) in the industrial domain, facilitating reuse and integration with other ontologies. Similarly, Cho *et al.* (2020) addressed the challenge of federating various data formats effectively using semantic technologies in the context of maintenance. The authors provided a formal terminology framework for maintenance strategies, enabling the development of computational agents to assist in the decision-making process for selecting and assessing maintenance strategies.

In the medical field, SWTs have also been instrumental. Sondes *et al.* (2019) developed an IoT-based healthcare monitoring system utilizing ontology for semantic interoperability. Tiwari and Abraham (2020) introduced the Smart Healthcare Ontology (SHCO), extracting healthcare knowledge for improved healthcare monitoring systems. Shishehchi and Banihashem (2021) and Banihashem and Shishehchi (2022) exploited SWTs for knowledge acquisition in the diagnosis of immune thrombocytopenia and fatty liver diseases. Moreover, researchers like Kumar (2015), Shahzad *et al.* (2021) and Alahmar *et al.* (2020) harnessed SWTs's capabilities for smart health services integration, ontological framework development and clinical pathways computerization, respectively. Yousefli *et al.* (2020) utilized SWTs to develop an automated multi-agent facility management system, enhancing maintenance workflows in hospitals through Unified Modeling Language (UML) and simulation.

While existing research has highlighted the advantages of SWTs, their applications in biomedical maintenance management have been notably scarce. Previous studies have primarily concentrated on the examination and optimization of individual healthcare systems, such as incubators and IRM devices, rather than emphasizing their maintenance. However, efficient maintenance management and resource allocation across all equipment are crucial for ensuring quality care. To bridge this gap, this paper seeks to develop a strategic medical equipment maintenance management system, aligning with the recommendations of Zamzam *et al.* (2021). The latter emphasized the significance of efficient management through the prioritization of medical equipment, enabling the assignment of appropriate maintenance strategies and allocation of sufficient resources. This work responds to this perspective by harnessing the advantages offered by SWTs.

3. Development of the proposed system

The acquisition of the required knowledge to build the system was orchestrated through the collaboration of field experts, comprising maintenance engineers, healthcare professionals and hospital management staff, with over 15 years of experience. Structured interview sessions were conducted to extract insights, supplementing available inventory reports and equipment sheets. The acquired knowledge is subsequently formalized and modeled using a customized ontology, derived from the widely recognized MASSON ontology (Lemaignan *et al.*, 2006), originally designed for manufacturing environments. The adopted ontology has undergone several adaptations to align with the distinctive specifications of healthcare facilities, encompassing various aspects, not only those pertinent to equipment maintenance. This imparts to the system the capability to function as a unified information portal across various hospital functions, rather than being limited exclusively to maintenance purposes. This broader functionality has the potential to enhance logistical support and overall facility management. Nonetheless, the maintenance function is distinguished than other functions by three integrated decision-support modules that serve the main purpose of the system by first assessing the criticality of medical equipment and subsequently determining appropriate maintenance strategies and contracting policies for each piece of equipment. Consequently, the system aspires to evolve into a KBS proficient in both information sharing and decision support. This is achieved through the utilization of both SWRL and SQWRL; SWRL integrates expert knowledge as a reference for assessment and appraisal, while SQWRL is employed for content inspection, inquiry and data retrieval. Consequently, the modeling method employed can be described as a domain knowledge-driven inference approach, as depicted in Figure 1.

The domain knowledge and the knowledge inference, illustrated in Figure 1, are coordinated through a structured framework for knowledge sharing and reusing, constituted of numerous components (Figure 2).

As depicted in Figure 2, the framework allows the entire ontology elements to work seamlessly and efficiently using four key integrated components that manage the knowledge-sharing process:

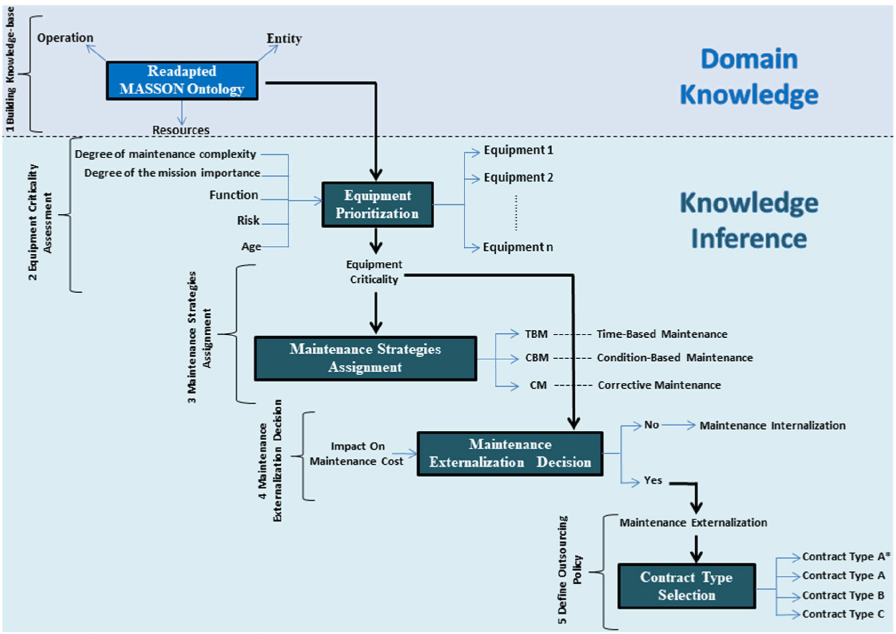

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Figure 1.
Concept of the proposed approach

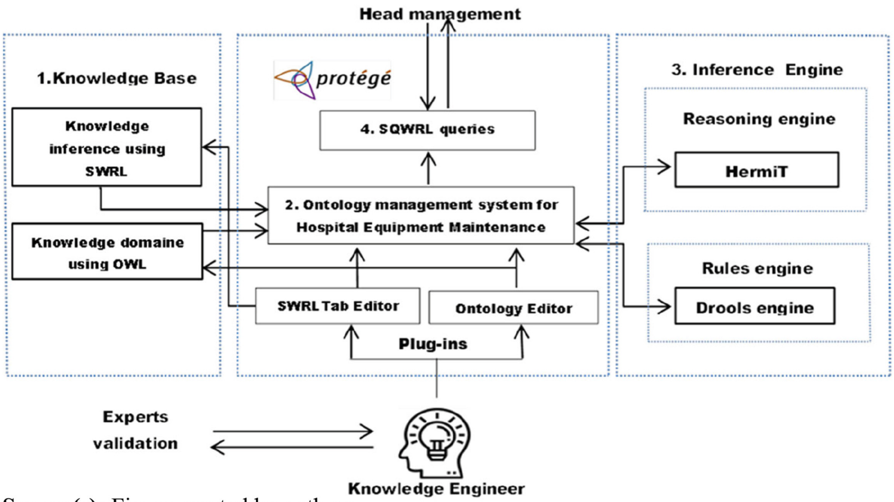

Figure 2.
Structure of the proposed model

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(1) **The knowledge base**: This is the most important component; it encompasses the whole knowledge associated with maintenance in healthcare facilities. It consists of the knowledge domain represented by the readapted MASSON ontology, which is expressed in OWL language, in addition to the knowledge inference expressed using SWRL rules, defined with the help of field experts, allowing to assess the equipment criticality, assign maintenance strategies and select the appropriate contract type.

(2) **The ontology management system:** In the case of the present study, this part was handled by Protégé (Noy *et al.*, 2003), which is a widely used software to establish and modify the ontology whenever needed.

(3) **The inference engine:** It divides into the reasoning engine and the rules engine, which respectively reads the existing facts and rules created by knowledge engineers and infers new facts in the system. In this case, the Hermit reasoning engine is used to check the consistency of the developed ontology in order to eliminate any potential errors, while the inference rules are handled by the Drools engine.

(4) **The query interface:** It is used to interact with the knowledge management system by means of the SQWRL rules, which allow to retrieve and display specific information at request.

From the above, the operating scenario of the proposed system can be described as follows. First, the related knowledge is capitalized and incorporated into the ontology. Then, the SWRL rules are defined (using SWRL tab in Protégé) and stored in the knowledge base. Next, the rules engine executes the SWRL rules and generates new facts in the ontology management system. Finally, the decision maker can exploit the outcome of these rules and get other useful information on demand by defining the associated constraints through the SQWRL query interface. The research tools and instruments employed for modeling, along with their specifications, are synthesized in Table 1. Further details regarding the model and the overall research methodology are subsequently expounded upon in the sub-sections below.

Ontology editor	Protégé 5.5.0: is a free open-source ontology editor supported by the National Institute of General Medical Sciences (https://protege.stanford.edu/)
Language used	OWL: an ontology web language for knowledge domain modeling SWRL: a semantic web rule language for knowledge inference modeling SQWRL: a semantic queries web rules language for knowledge domain selecting
Rules engine	The Drools rule engine is an essential tool for developing rules that can be applied repeatedly to a set of facts or run to create new facts
Reasoning engine	Hermit: is a vital reasoner in ontology. It can provide important standards and advanced reasoning services
Plug-ins	SWRL Tab: helps to write SWRL rules and runs Drools for rules execution SQWRLTab: helps to write SQWRL queries for user interface and uses Drools for query execution

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Table 1. Model specifications

3.1 Formalization of domain knowledge

As aforementioned, the adopted formalization of the knowledge domain is inspired by the ontological representation MASSON (Lemaignan *et al.*, 2006), which is based on three fundamental concepts "Operation," "Resources" and "Entity," each of which is divided into several classes and subclasses.

To begin with, the "Material resources" class issued from MASSON's "Resources" concept is redefined as the "Equipment" class, encompassing all the instruments and the devices within the hospital, organized into subclasses based on the respective medical departments they serve, such as radiotherapy, radiology, biochemistry, etc., as illustrated in Figure 3.

On the other hand, the "Human-Resource" class was maintained, while readapting its inner subclasses according to the different personnel categories of healthcare facilities such as managers, doctors, nurses, patients, interns, etc., as demonstrated in Figure 4.

Similarly, the "Operation-Maintenance" class is created by inspiration from the "Manufacturing-Operation" concept of Lin *et al.* (2011) and the "Operation class" of Lemaignan *et al.* (2006). It is divided into two inner subclasses "Internalization" and "Externalization" (Figure 5), representing the maintenance outsourcing decision for each equipment.

The "Method" and "Contract" concepts (Figure 6) are based on the "Technological entity" concept defined by Lemaignan *et al.* (2006). While the same maintenance methods applied to industrial maintenance are applied to biomedical maintenance, it is more often resorted to outsourcing in the latter to cover associated tasks due to the limited technical staff in terms of both number and gear. Therefore, the "Maintenance-Method" class contains two subclasses "CorrectiveMaintenance" and "PreventiveMaintenance," representing the two well-known types of maintenance strategies. On the other hand, the "Contract-Maintenance" class contains four subclasses representing the different maintenance outsourcing policies adopted in this field: "TypeA*," "TypeA," "TypeB" and "TypeC" (refer to section 3.2.3 below for their detailed description). Figure 6 illustrates these classes and their hierarchies.

Figure 7 below illustrates the main classes of the whole model and their class hierarchies along with their inter-relations.

The inter-relations among the different classes/subclasses are defined through the "Object properties" tab of the ontology editor, while their respective data are stored in the "Data properties" tab in the form of a set of quantitative parameters and indicators. For example, Figure 8 demonstrates the instances related to the "Radiology-equipment" subclass (Part a) along with the relevant data properties (Part b) and object properties (Part c).

3.2 Formalization of knowledge inference

The knowledge inference of the model is divided into three integrated rule-based reasoning decision-support modules that handle the equipment criticality assessment, the assignment

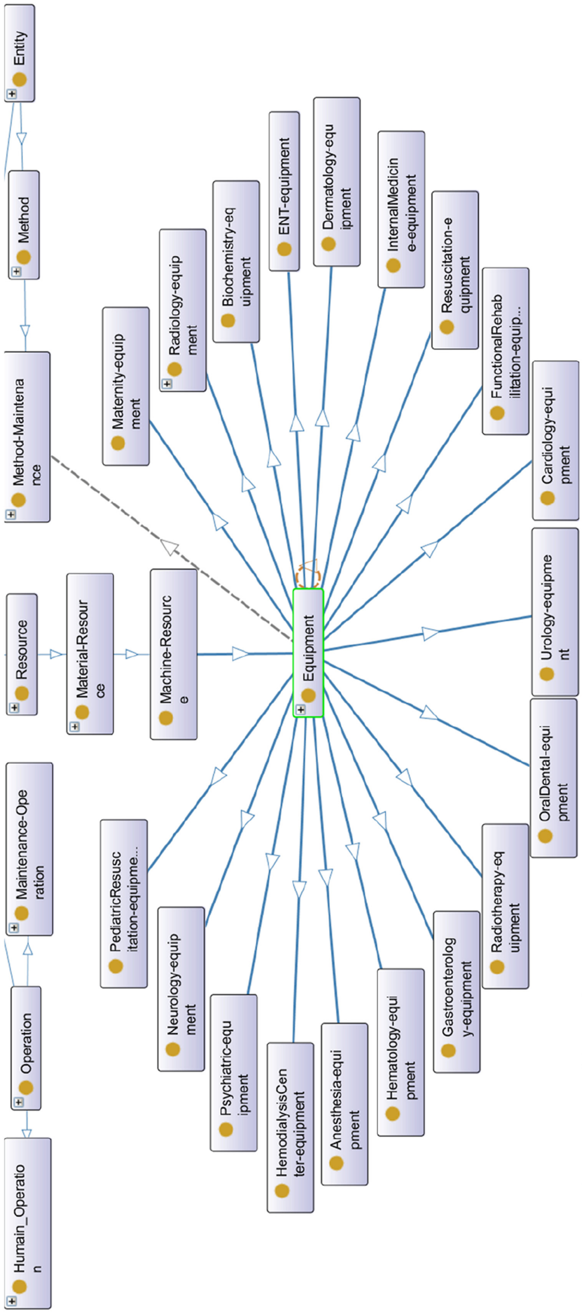

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Figure 3.
The "Equipment" class and its network of subclasses

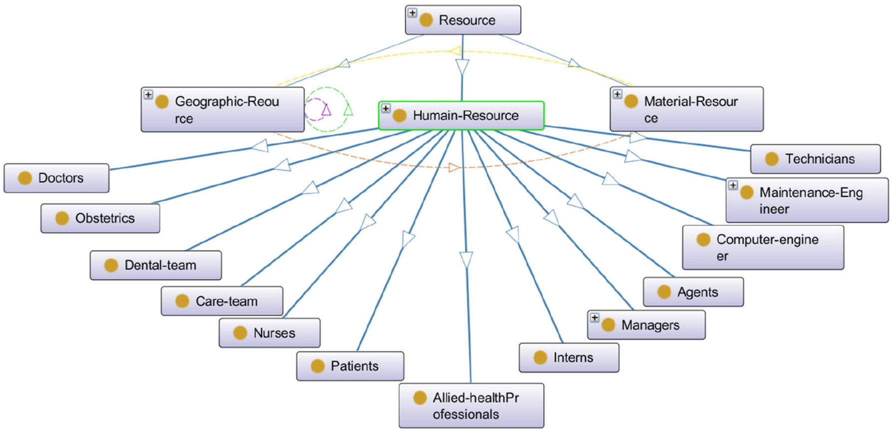

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Figure 4. The "Human resources" class and its network of subclasses

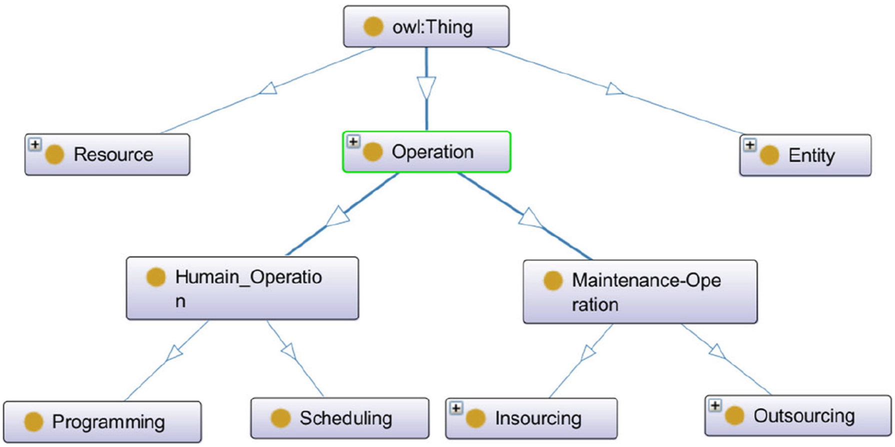

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Figure 5. The "Operation" class and its network of subclasses

of their maintenance strategies and the selection of their respective maintenance contracting policies. The three modules rely on SWRL rules and the Drools inference engine for information processing. Their workflow is described per module in the sub-sections below.

3.2.1 Criticality assessment. The initial module evaluates the criticality of healthcare equipment using a multicriteria perspective to precisely identify top-priority items for maintenance actions. These actions include scheduling preventive repairs, outsourcing, ordering spare parts and considering other potentially required investments. The criteria for this assessment are established through a review of pertinent literature and further enriched and validated through discussions with field specialists from the maintenance department at the UHC of Oran. Notably, these specialists are also actively engaged in the development of the evaluation metrics, in addition to the required scales for assessing qualitative aspects within the entire process of formalizing inference rules. In total, five criteria are considered for the assessment of equipment criticality:

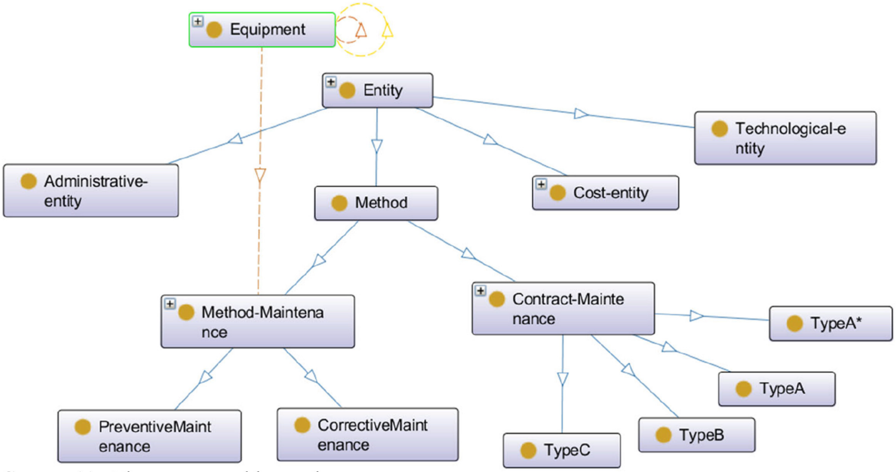

Figure 6.
The "Method" class and its network of subclasses

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(1) **Degree of mission importance:** It represents the extent to which the device is needed by medical professionals, in order to be able to perform their duty. It is quantified based on the equipment utilization rate (UR) (average weekly usage hours divided by the maximum), following three levels: high, medium and low, as expressed in the rules below (Table 2).

(2) **Function:** It represents the purpose for which a medical device is mainly used, for example, diagnosis, life support, monitoring, etc. (refer to Table 3 for explicit listing of equipment categories). Different devices may have different impacts on the health and safety of patients. Obviously, some functions are more critical than others. Following this logic, each function is given a respective score reflecting its importance, using the SWRL rules below (Table 3).

(3) **Degree of maintenance complexity:** Medical devices implement various technologies that obviously differ in terms of complexity and thus also maintenance difficulty. This criterion is aimed at quantifying this complexity according to the equipment type (advanced mechanical, pneumatic or hydraulic) and its maintenance perquisites, such as the need to conduct advanced performance and safety tests or just assessing the physical state of the asset visually, which is translated into the rules below (Table 4).

(4) **Risk:** It represents the potential impact of a medical device failure on the patients' health and safety. This criterion is evaluated taking into account the criticality of the function of each device (the FS scores calculated using the rules of Table 3), with the highest risk score directly assigned to the devices covering the top critical functions (life support, surgical-intensive care, physical therapy treatment, intensive care monitoring and physiological diagnosis), while the risk associated with the devices serving in the remaining functions is assessed using the risk priority number (RPN) method, issuing from the well-known Failure Modes Effects and Criticality Analysis (FMECA) in maintenance. The RPN is defined as the product of three failure characteristics, which are the frequency of occurrence (O), the severity (S) and the detectability (D), where the device failure rate, its availability and its maintenance complexity degree are, respectively, selected as the reflective parameters for these characteristics, with the adoption of a three-level (high,

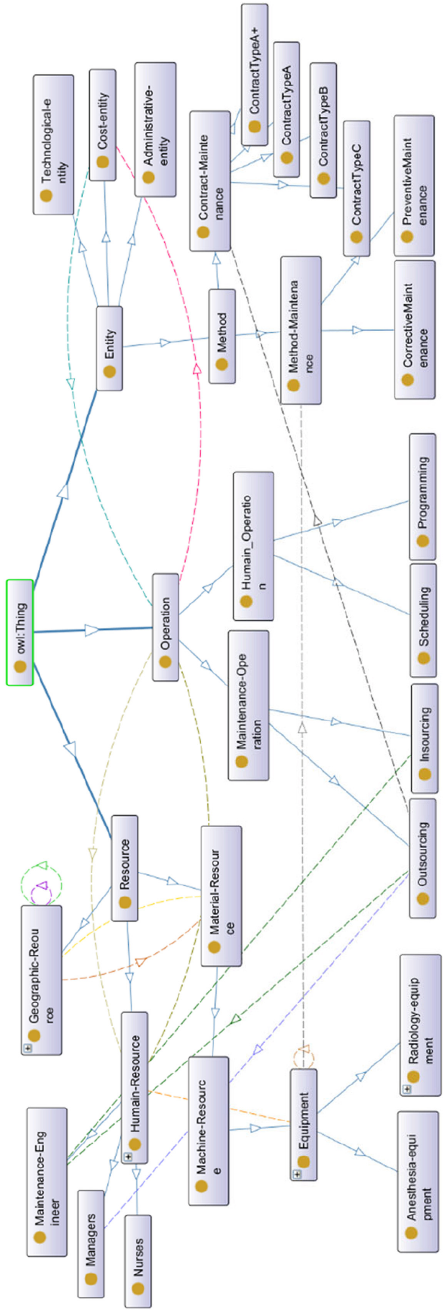

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Figure 7.
Main classes adapted from MASSON ontology and its hierarchies subclasses

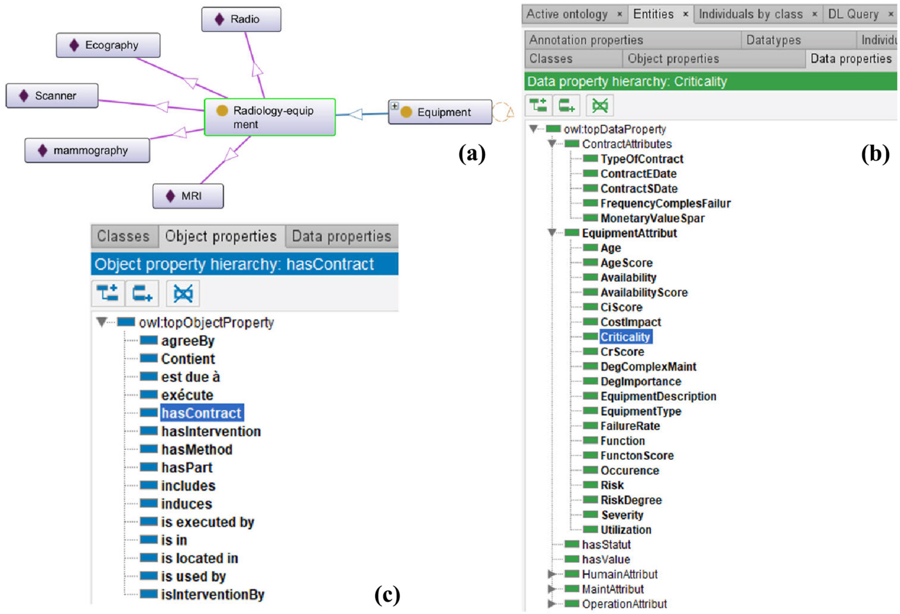

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Figure 8. Instances of the "Radiology-equipment" subclass (a) with the associated data properties (b) and object properties (c)

medium and low) rating scale to evaluate and standardize these parameters. Table 5 below lists the rules used for assessing the risk criterion, while Tables 6 and 7 list the rules used for the evaluation of the first two parameters (O and S). As for the third parameter (D), the outputs of the rules previously defined in Table 4 are directly exploited, since they are consistent with the adopted evaluation process.

(5) **Age:** It represents the time elapsed in years since the commissioning of the equipment, which is considered as a relative indicator of the actual condition of the equipment and its reliability. Considering that most medical devices are subject to significant degradation due to heavy usage and frequent user errors, each device older than 10 years of service is given an age score of 2, while the opposite case gets a score of 1, as expressed by the rules in Table 8.

After evaluating the equipment according to all the criteria, it is possible to quantify and assess its overall criticality, which is defined as a sum function of the scores obtained under each criterion. The rules used for this purpose are listed in Table 9 below.

The quantified criticality values (C) can be used as a key indicator to prioritize the equipment and manage maintenance tasks accordingly, with the aim of maximizing the effectiveness of its actions and improving the hospital service quality, while the assigned criticality levels (high, medium and low) are meant to help in categorizing the equipment and grouping maintenance activities.

3.2.2 Maintenance strategies assignment. The second module exploits the resulting criticality assessment outputs to assign the proper maintenance strategy for each piece of equipment. In this context, three main strategies are considered:

(1) **Corrective maintenance (CM):** It involves repairing or fixing a piece of equipment or a system after it has failed or malfunctioned, with the aim of restoring it to its standard operational state. This approach does not require additional labor or a

Rule 1	Rating of the equipment mission importance degree score (di) based on the equipment UR
Rule 1.1	If UR ≥ 70%, then the importance degree score is 3 *Equipment(?E) ^ Utilization(?E, ?ur) ^ DegImportance(?E, ?di) ^ swrlb:greaterThanOrEqual(?ur, 70) → DegImportance(?E, 3)*
Rule 1.2	If the device degree score is 3, then its degree of mission importance is high *Equipment(?E) ^ DegImportance(?E, 3) → hasStatut(?di, "high")*
Rule 1.3	If 40% < UR < 70%, then the importance degree score is 2 *Equipment(?E) ^ Utilization(?E, ?ur) ^ DegImportance(?E, ?di) ^ swrlb:greaterThan(?ur, 40)^ swrlb:lessThan(?y,70) → DegImportance(?E, 2)*
Rule 1.4	If the device degree score is 2, then its degree of the mission importance is medium *Equipment(?E) ^ DegImportance(?E, 2) → hasStatut(?di, "medium")*
Rule 1.5	If UR ≤ 40%, then the importance degree score is 1 *Equipment(?E) ^ Utilization(?E, ?ur) ^ DegImportance(?E, ?di) ^ swrlb:lessThanOrEqual(?ur,40) → DegImportance(?E, 1)*
Rule 1.6	If the device degree score is 1, then its degree of mission importance is low *Equipment(?E) ^ DegImportance(?E, 1) → hasStatut(?di, "low")*

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Table 2. SWRL rules used for assessing the mission importance degree criterion

Rule 2	Assignment of a FS to the equipment reflecting its function importance
Rule 2.1	If the equipment belongs to "Life Support" category, its FS is 9 *Equipment(?E) ^ Function(?E, "LifeSupport") ^ FunctionScore(?E, ?FS) → FunctionScore(?E, 9)*
Rule 2.2	If the equipment belongs to "Surgical-intensive Care" category, its FS is 8 *Equipment(?E) ^ Function(?E, "Surgical-intensiveCare") ^ FunctionScore(?E, ?FS) → FunctionScore(?E, 8)*
Rule 2.3	If the equipment belongs to "Physical Therapy Treatment" category, its FS is 7 *Equipment(?E) ^ Function(?E, "PhysicalTherapyTreatment") ^ FunctionScore(?E, ?FS) → FunctionScore(?E, 7)*
Rule 2.4	If the equipment belongs to "Surgical-intensive Care Monitoring" category, its FS is 6 *Equipment(?E) ^ Function(?E, "Surgical-intensiveCareMonitoring") ^ FunctionScore(?E, ?FS) → FunctionScore(?E, 6)*
Rule 2.5	If the equipment belongs to "Physiological Diagnosis" category, its FS is 5 *Equipment(?E) ^ Function(?E, "PhysiologicalDiagnosis") ^ FunctionScore(?E, ?FS) → FunctionScore(?E, 5)*
Rule 2.6	If the equipment belongs to "Analytical Laboratory" category, its FS is 4 *Equipment(?E) ^ Function(?E, "AnalyticalLaboratory") ^ FunctionScore(?E, ?FS) → FunctionScore(?E, 4)*
Rule 2.7	If the equipment belongs to "Laboratory Accessories" category, its FS is 3 *Equipment(?E) ^ Function(?E, "LaboratoryAccessories") ^ FunctionScore(?E, ?FS) → FunctionScore(?E, 3)*
Rule 2.8	If the equipment belongs to "Computer Related" category, its FS is 2 *Equipment(?E) ^ Function(?E, "ComputerRelated") ^ FunctionScore(?E, ?FS) → FunctionScore(?E, 2)*
Rule 2.9	If the equipment belongs to "Patient Related and Other" category, its FS is 1 *Equipment(?E) ^ Function(?E, "PatientRelated") ^ FunctionScore(?E, ?FS) → FunctionScore(?E, 1)*

Source(s): Table created by authors

Table 3. SWRL rules used for assessing the function criterion

special budget to be implemented. However, the random downtime caused by equipment failures and the overuse of labor to carry out repairs can result in significant costs and considerable inconvenience or even serious consequences in some cases.

(2) **Condition-based maintenance (CBM):** It involves evaluating the operational condition of a system, regularly or on real-time, with the aim of detecting potential failures before they occur and applying timely effective fixes. To implement CBM,

Rule 3	Rating the equipment degree of maintenance complexity (dc)
Rule 3.1	If the equipment type is advanced mechanical, pneumatic or hydraulic, the degree of complexity is 3 *Equipment(?E) ^ EquipmentType(?E, "advancedMechanicalEquip") ^ DegComplexMaint(?E, ?dc) → DegComplexMaint(?E, 3)* *Equipment(?E) ^ EquipmentType(?E, "pneumaticEquip") ^ DegComplexMaint(?E, ?dc) → DegComplexMaint(?E, 3)* *Equipment(?E) ^ EquipmentType(?E, "hydraulicEquip") ^ DegComplexMaint(?E, ?dc) → DegComplexMaint(?E, 3)*
Rule 3.2	If the maintenance complexity degree is rated 3, then it is considered high *Equipment(?E) ^ DegComplexMaint(?E, 3) → hasStatut(?dc, "high")*
Rule 3.3	If the equipment type requires performance verification or safety tests, the degree of complexity is 2 *Equipment(?E) ^ EquipmentType(?E, "PerformanceTests") ^ DegComplexMaint(?E, ?dc) → DegComplexMaint(?E, 2)* *Equipment(?E) ^ EquipmentType(?E, "SafetyTests") ^ DegComplexMaint(?E, ?dc) → DegComplexMaint(?E, 2)*
Rule 3.4	If the maintenance complexity degree is rated 2, then it is considered medium *Equipment(?E) ^ DegComplexMaint(?E, 2) → hasStatut(?dc, "medium")*
Rule 3.5	If the equipment type requires only visual inspections, the degree of complexity is 1 *Equipment(?E) ^ EquipmentType(?E, "VisualTests" ^ DegComplexMaint(?E, ?dc) → DegComplexMaint(?E, 1)*
Rule 3.6	If the maintenance complexity degree is rated 1, then it is considered low *Equipment(?E) ^ DegComplexMaint(?E, 1) → hasStatut(?dc, "low")*

Source(s): Table created by authors

Table 4.
SWRL rules used for assessing the equipment maintenance complexity degree criterion

Rule 4	Quantification of the risk (R) associated with equipment malfunction and assessment of its degree
Rule 4.1	R = Occurrence × Severity × DegComplexMaint | (where the latter reflects the detectability) *Equipment(?E) ^ Occurrence (?E, ?O) ^ Severity (?E, ?S)^ DegComplexMaint (?E, ?dc) ^ Risk(?E, ?R) ^ swrlb:multiply (?R, ?O, ?S, ?dc) → Risk (?E, ?R)*
Rule 4.2	If $1 \le FS < 6$, and $R < 20$, then the device risk degree is 1 *Equipment(?E) ^ RiskDegree (?E, ?r) ^ Risk (?E,?R) ^ FunctionScore(?E,?FS) ^ swrlb:greaterThanOrEqual(?FS, 1) ^ swrlb:lessThan(?FS,6) ^ swrlb:lessThanOrEqual(?R,20) → RiskDegree (?E, 1)*
Rule 4.3	If the risk degree is 1, then the associated riskiness is low *Equipment(?E) ^ RiskDegree (?E, 1) → hasStatut(?R, "low")*
Rule 4.4	If $1 \le FS < 6$, and $20 < R \le 36$, then the device risk degree is 2 *Equipment(?E) ^ RiskDegree (?E, ?r) ^ Risk (?E,?R) ^ FunctionScore(?E,?FS) ^ swrlb:greaterThanOrEqual(?FS, 1) ^ swrlb:lessThan(?FS,6) ^ swrlb:greaterThan(?R, 20) ^ swrlb:lessThanOrEqual (?R,36) → RiskDegree (?E, 2)*
Rule 4.5	If the risk degree is 2, then the associated riskiness is medium *Equipment(?E) ^ RiskDegree (?E, 2) → hasStatut(?R, "medium")*
Rule 4.6	If $1 \le FS < 6$, and $R > 36$, then the device risk degree is 3 *Equipment(?E) ^ RiskDegree (?E, ?r) ^ Risk(?E,?R) ^ FunctionScore(?E,?FS) ^ swrlb:greaterThanOrEqual(?FS, 1) ^ swrlb:lessThan(?FS,6) ^ swrlb:greaterThan(?R, 36) → RiskDegree (?E, 3)*
Rule 4.7	If the risk degree is 3, then the associated riskiness is high *Equipment(?E) ^ RiskDegree (?E, 1) → hasStatut(?R, "high")*
Rule 4.8	If $5 < FS \le 9$, then the device receives directly the highest risk degree score which is 4 *Equipment(?E) ^ RiskDegree (?E, ?r) ^ Risk (?E,?R) ^ FunctionScore(?E,?FS) ^ swrlb:greaterThan(?FS, 5) ^ swrlb:lessThanOrEqual(?FS,9) → RiskDegree (?E, 4)*
Rule 4.9	If the risk degree is 4, then the associated riskiness is very high *Equipment(?E) ^ RiskDegree (?E, 4) → hasStatut(?R, "very high")*

Source(s): Table created by authors

Table 5.
SWRL rules used for assessing the risk criterion

	Assessment of the occurrence parameter based on the equipment failure rate (F)
Rule 4.1.1	If $1 \leq FS < 6$, and $F \leq 0.001$, then the occurrence degree is 1 *Equipment(?E) ^ FailureRate(?E, ?F) ^ FunctionScore(?E,?FS) ^ Occurrence(?E, ?O) ^ swrlb:greaterThanOrEqual(?FS, 1) ^ swrlb:lessThan(?FS,6) ^ swrlb:lessThanOrEqual(?F, 0.001) → Occurrence(?E, 1)*
Rule 4.1.2	If the occurrence degree is 1, then the frequency of failure is low *Equipment(?E) ^ Occurrence(?E, 1) → hasStatut(?O, "low")*
Rule 4.1.3	If $1 \leq FS < 6$, and $0.001 < F < 0.004$, then the occurrence degree is 2 *Equipment(?E) ^ FailureRate(?E, ?F) ^ FunctionScore(?E,?FS) ^ Occurrence(?E, ?O) ^ swrlb:greaterThanOrEqual(?FS, 1) ^ swrlb:lessThan(?FS,6) ^ swrlb:greaterThan(?F, 0.001) ^ swrlb:lessThan(?F,0.004) → Occurrence(?E, 2)*
Rule 4.1.4	If the occurrence degree is 2, then the frequency of failure is medium *Equipment(?E) ^ Occurrence(?E, 2) → hasStatut(?O, "medium")*
Rule 4.1.5	If $1 \leq FS < 6$, and $F \geq 0.004$, then the occurrence degree is 3 *Equipment(?E) ^ FailureRate(?E, ?F) ^ FunctionScore(?E,?FS) ^ Occurrence(?E, ?O) ^ swrlb:greaterThanOrEqual(?FS, 1) ^ swrlb:lessThan(?FS,6) ^ swrlb:greaterThanOrEqual(?F, 0.004) → Occurrence(?E, 3)*
Rule 4.1.6	If the occurrence degree score is 1, then the frequency of failure is high *Equipement(?E) ^ Occurrence(?E,3) → hasStatut(?O, "high")*

Source(s): Table created by authors

Table 6. SWRL rules used for quantifying the occurrence frequency parameter (O) of the risk criterion

	Assessment of the severity parameter based on the equipment availability (A)
Rule 4.1.7	If $1 \leq FS < 6$, and $A < 85\%$, then the severity score is 1 *Equipment(?E) ^ Availability (?E,?A) ^ FunctionScore(?E,?FS) ^ Severity(?E, ?S) ^ swrlb:greaterThanOrEqual(?FS, 1) ^ swrlb:lessThan(?FS,6) ^ swrlb:lessThan(?A,0.85) → Severity(?E, 1)*
Rule 4.1.8	If the severity score is 1, then then the severity level is low *Equipment(?E) ^ Severity(?E, 1) → hasStatut(?S, "low")*
Rule 4.1.9	If $1 \leq FS < 6$, and $85\% \leq A < 95\%$, then the severity score is 2 *Equipment(?E) ^ Availability (?E,?A) ^ FunctionScore(?E,?FS) ^ Severity(?E, ?S) ^ swrlb:greaterThanOrEqual(?FS, 1) ^ swrlb:lessThan(?FS,6) ^ swrlb:greaterThanOrEqual(?A, 85) ^ swrlb:lessThan(?A,0.95) → Severity(?E, 2)*
Rule 4.1.10	If the severity score is 2, then the severity level is medium *Equipment(?E) ^ Severity(?E, 2) → hasStatut(?S, "midium")*
Rule 4.1.11	If $1 \leq FS < 6$, and $A \geq 95\%$, then the severity score is 3 *Equipment(?E) ^ Availability (?E,?A) ^ FunctionScore(?E,?FS) ^ Severity(?E, ?S) ^ swrlb:greaterThanOrEqual(?FS, 1) ^ swrlb:lessThan(?FS,6) ^ swrlb:greaterThanOrEqual(?A, 0.95) → Severity(?E, 3)*
Rule 4.1.12	If the severity score is 3, then the severity level is high *Equipment(?E) ^ Severity(?E, 1) → hasStatut(?S, "high")*

Source(s): Table created by authors

Table 7. SWRL rules used for quantifying the severity parameter (S) of the risk criterion

specialized sensors are needed to assess deterioration, measure prediction variables or analyze data on the system's performance, such as vibration, temperature and other key indicators. Additionally, a statistical model may be required to establish a correlation between the measured variables and the health of the equipment, such as its remaining useful life. By catching issues early, this strategy can help in reducing downtime and extend the lifespan of the equipment or system. However, it requires acquiring the necessary measuring tools and instruments, as well as having sufficient knowledge of measurement techniques and/or degradation models.

(3) **Time-based maintenance (TBM):** It involves conducting regular checks, calibrations, lubrification, replacements or other maintenance activities on

equipment on a routine basis (fixed intervals of elapsed operating time, usage times counter or other specific criteria). TBM can help ensure the equipment or system continues to operate reliably and efficiently by preventing failures and malfunctions. Nonetheless, this approach may result in unnecessary maintenance if the equipment or system is still in good condition. Furthermore, it necessitates dedicated resources, such as funding and workforce, for proper implementation.

The rules used for assigning these strategies to the equipment, based on the predefined criticality degree scores, are listed in Table 10 below.

Table 8. SWRL rules used for assessing the age criterion

Rule 5	Evaluation of the equipment age according to the number of years elapsed since commissioning
Rule 5.1	If the age of the equipment is less than or equal to 10 years, it receives a score of 1 *Equipment(?E) ^ Age(?E, ?ag) ^ swrlb:lessThanOrEqual(?ag,10) → AgeScore(?E, 1)*
Rule 5.2	If the age of the equipment is more than 10 years, it receives a score of 2 *Equipment(?E) ^ Age(?E, ?ag) ^ swrlb:greaterThan(?ag,10 → AgeScore(?E, 2)*

Source(s): Table created by authors

Table 9. SWRL rules used for assessing the equipment overall criticality

Rule 6	Multicriteria quantification of the overall equipment criticality (C) and assessment of its level
Rule 6.1	C = DegComplexMaint + FunctionScore + RiskDegree + DegImportance + AgeScore *Equipment(?E) ^ DegComplexMaint(?E, ?dc) ^ FunctionScore(?E, ?fc) ^ RiskDegree(?E, ?r) ^ DegImportance(?E, ?di) ^ AgeScore(?E, ?as) ^ swrl:add(?C, ?dc, ?fc, ?r, ?di, ?as → Criticality (?E, ?C)*
Rule 6.2	If C ≥ 18, then the device gets a criticality degree score (Cr) of 3 *Equipment(?E) ^ Criticality (?E, ?C) ^ CrScore (?E, ?Cr) ^ swrlb:greaterThanOrEqual(?C, 18)) → CrScore(?E, 3)*
Rule 6.3	If the criticality score is 3, then the criticality level is high *Equipment(?E) ^ CrScore(?Cr, 3) → hasStatut(?Cr, "high")*
Rule 6.4	If 12 ≤ C < 18, then the device gets a criticality degree score (Cr) of 2 *Equipment(?E) ^ Criticality (?E, ?C) ^ CrScore (?E, ?Cr) ^ swrlb:greaterThanOrEqual(?C, 12) ^ swrlb:lessThan(?C,18) → CrScore(?E, 2)*
Rule 6.5	If the criticality score is 2, then the criticality level is high *Equipment(?E) ^ CrScore(?Cr, 2) → hasStatut(?Cr, "medium")*
Rule 6.6	If C < 12, then the device gets a criticality degree score (Cr) of 1 *Equipment(?E) ^ Criticality (?E, ?C) ^ CrScore (?E, ?Cr) ^ swrlb:lessThan(?C,12) → CrScore(?E, 1)*
Rule 6.7	If the criticality score is 1, then the criticality level is low *Equipment(?E) ^ CrScore(?Cr, 1) → hasStatut(?Cr, "low")*

Source(s): Table created by authors

Table 10. SWRL rules used for assigning maintenance strategies for the equipment

Rule 7	Assigning appropriate maintenance strategies for hospital equipment according to the criticality degree
Rule 7.1	If the device criticality level is high, then the suitable maintenance strategy is "Time-based maintenance" *Equipment(?E) ^ hasStatut(?Cr, "high") ^ Method-Maintenance(?MM) ^ hasMethod(?E, ?MM) → Maintenance-Method(TBM)*
Rule 7.2	If the device criticality level is medium, then the suitable maintenance strategy is "Condition-based maintenance" *Equipment(?E) ^ hasStatut(?Cr, "medium") ^ Method-Maintenance(?MM) ^ hasMethod(?E, ?MM) → Maintenance-Method(Condition-based maintenance)*
Rule 7.3	If the device criticality level is low, then the suitable maintenance strategy is "CM" *Equipment(?E) ^ hasStatut(?Cr, "low") ^ Method-Maintenance(?MM) ^ hasMethod(?E, ?MM) → Maintenance-Method(Corrective Maintenance)*

Source(s): Table created by authors

3.2.3 Maintenance-contract type selection. The third and last module deals with the maintenance externalization decision, including the selection of an appropriate contracting policy for each externally maintained device. In developing countries, including the country in which the current study is conducted, there are generally four types of contracts to choose from (Masmoudi *et al.*, 2016):

(1) **Type A*:** Full package contract with all risks covered and all maintenance tasks, both corrective and preventive, performed by the subcontractor.

(2) **Type A:** It covers all TBM tasks, including both spare parts and labor.

(3) **Type B:** It involves the tasks related to either TBM, CBM or both of them combined and covers only the spare parts.

(4) **Type C:** It involves on-demand interventions, with neither spare parts nor labor costs covered under the contract. It is usually assigned to equipment known for its complex failures.

The selection of the appropriate contract type for each medical device is based on the rules below (Table 11), which rely on the predefined criticality scores in addition to the equipment's economic

Rule 8	Handling contracting decisions based on the criticality level and the impact on maintenance cost
Rule.8.1	If the equipment criticality score is 3, the maintenance cost impact is 3, then the type of contact is Type A* *Equipment(?E) ^ CrScore(?E, ?Cr) ^ CiScore(?E, ?Ci) ^ hasValue(?Cr, 3) ^ hasValue(?Ci, 3) → TypeOfContract(?E, ?cm) ^ hasValue(?cm, TypeA*)*
Rule.8.2	If the equipment criticality score is 3 and the maintenance cost impact is 2, then the type of contact is Type A* *Equipment(?E) ^ CrScore(?E, ?Cr) ^ CiScore(?E, ?Ci) ^ hasValue(?Cr, 3) ^ hasValue(?Ci, 2) → TypeOfContract(?E, ?cm) ^ hasValue(?cm, TypeA*)*
Rule.8.3	If equipment criticality score is 3 and maintenance cost impact is 1, then type of contact is Type A *Equipment(?E) ^ CrScore(?E, ?Cr) ^ CiScore(?E, ?Ci) ^ hasValue(?Cr, 3) ^ hasValue(?Ci, 1) → TypeOfContract(?E, ?cm) ^ hasValue(?cm, TypeA)*
Rule.8.4	If the equipment criticality score is 2 and the maintenance cost impact is 3, then the type of contact is Type B *Equipment(?E) ^ CrScore(?E, ?Cr) ^ CiScore(?E, ?Ci) ^ hasValue(?Cr, 2) ^ hasValue(?Ci, 3) → TypeOfContract(?E, ?cm) ^ hasValue(?cm, TypeC)*
Rule.8.5	If equipment criticality score is 2 and maintenance cost impact is 2, then type of contact is Type B *Equipment(?E) ^ CrScore(?E, ?Cr) ^ CiScore(?E, ?Ci) ^ hasValue(?Cr, 2) ^ hasValue(?Ci, 2) → TypeOfContract(?E, ?cm) ^ hasValue(?cm, TypeC)*
Rule.8.6	If the equipment criticality score is 2 and the maintenance cost impact is 1, then the type of contact is Type C *Equipment(?E) ^ CrScore(?E, ?Cr) ^ CiScore(?E, ?Ci) ^ hasValue(?Cr, 2) ^ hasValue(? Ci, → TypeOfContract(?E, ?cm) ^ hasValue(?cm, TypeC)*
Rule.8.7	If the equipment criticality score is 1 and the maintenance cost impact is 3, then the type of contact is Type C *Equipment(?E) ^ CrScore(?E, ?Cr) ^ CiScore(?E, ?Ci) ^ hasValue(?Cr, 1) ^ hasValue(?Ci, 3) → TypeOfContract(?E, ?cm) ^ hasValue(?cm, TypeC)*
Rule.8.7	If the equipment criticality score is 1 and the maintenance cost impact is 2, then there is no contracting (maintenance internalization) *Equipment(?E) ^ CrScore(?E, ?Cr) ^ CiScore(?E, ?Ci) ^ hasValue(?Cr, 1) ^ hasValue(?Ci, 2) → TypeOfContract(?E, ?cm) ^ hasValue(?cm, NoContract)*
Rule.8.8	If the equipment criticality score is 1 and the maintenance cost impact is 1, then there is no contracting (maintenance internalization) *Equipment(?E) ^ CrScore(?E, ?Cr) ^ CiScore(?E, ?Ci) ^ hasValue(?Cr, 1) ^ hasValue(?Ci, 1) → TypeOfContract(?E, ?cm) ^ hasValue(?cm, NoContract)*

Source(s): Table created by authors

Table 11. SWRL rules used for handling outsourcing decisions and contract type selection

impact on maintenance (the ratio among the device's annual maintenance cost and the total maintenance cost), where the latter is assessed using the rules listed in Table 12 beneath.

3.3 Information retrieval and query processing

After undergoing a consistency check using Hermit reasoner, the facts inferred to the knowledge base from the model by the three modules previously described can be retrieved using SQWRL queries. These queries allow the definition of various constraints for selecting and filtering outputs, which ensures the extraction of useful information upon request. Table 13 describes some of the SQWRL queries incorporated, covering the main functions of the model.

4. Implementation of the proposed system

4.1 Preview of the implemented model

The developed KBS is implemented within the UHC of Oran with the aim of testing its applicability and efficiency in maintenance management. For the sake of conciseness, 20 pieces of equipment, belonging to different hospital departments, are considered for the study. The selection of equipment is informed by the expertise of field specialists and is guided by insights

	Assessment of the equipment impact on maintenance cost (CI) and its degree
Rule 8.1.1	If CI ≥ 9%, then the device gets a cost impact score of 3 *Equipment(?E) ^ CostImpact(?E, ?CI) ^ CiScore(?E, ?Ci) ^ swrlb:greaterThanOrEqual(?CI, 0.09) → CiScore(?E, 3)*
Rule 8.1.2	If the cost impact score is 3, then degree of the cost Impact is high *Equipment(?E) ^ CiScore(?E, 3) → hasStatut(?Ci, "high")*
Rule 8.1.3	If 5% ≤ CI < 9%, then the device gets a cost impact score of 2 *Equipment(?E) ^ CostImpact(?E, ?CI) ^ CiScore(?E, ?Ci) ^ swrlb:greaterThanOrEqual(?CI, 0.05)^ swrlb:lessThan(?CI,0.09) → CiScore(?E, 2)*
Rule.8.1.4	If the cost impact is 2, then degree of the cost impact is high *Equipment(?E) ^ CiScore(?E, 2) → hasStatut(?Ci, "medium")*
Rule 8.1.5	If CI < 5%, then the device gets a cost impact score of 1 *Equipment(?E) ^ CostImpact(?E, ?CI) ^ CiScore(?E, ?Ci) ^ swrlb:lessThan(?CI,0.05) → CiScore(?E, 1)*
Rule 8.1.6	If the cost impact is 1, then degree of the cost impact is low *Equipment(?E) ^ CiScore(?E, 1) → hasStatut(?Ci, "low")*

Source(s): Table created by authors

Table 12.
SWRL rules used for assessing the equipment impact on maintenance cost

Rule 1	Selecting equipment with consideration over all criticality and inner criticality factors *Equipment(?E) ^ Criticality(?E, ?C) ^ Utilization(?E, ?ur) ^ EquipmntType(?E, ?t) ^ Function(?E, ?f) ^ Risk(?E, ?R)) ^ Age(?E, ?ag) → sqwrl:select(?E, ?C,?ur,?t, ?f, ?R, ?ag)*
Rule 2	Selecting equipment with consideration of criticality and maintenance method *Method-Maintenance(?MM) ^ Equipment(?E) ^ hasMethod(?E, ?MM) ^ Criticality(?E, ?C) → sqwrl:select(?E, ?C, ?MM)*
Rule 3	Selecting equipment concerned with internal maintenance *Equipment(?E) ^ Criticality(?E, ?C) ^ TypeOfContract(?E,?cm) ^ hasValue(?cm, "NoContract") → sqwrl:select(?E, ?C, ?cm)*
Rule 4	Selecting equipment concerned with external maintenance *Equipment(?E) ^ Criticality(?E, ?C) ^ TypeOfContract(?E,?cm) → sqwrl:select(?E, ?Cr, ?cm)*
Rule 5	Selecting equipment with consideration of contract type, criticality and impact on maintenance cost *Equipment(?E) ^ Criticality(?E, ?C) ^ TypeOfContract(?E,?cm) ^ CostImpact(?E, ?CI)) → sqwrl:select(?E, ?C,?CI, ?cm)*

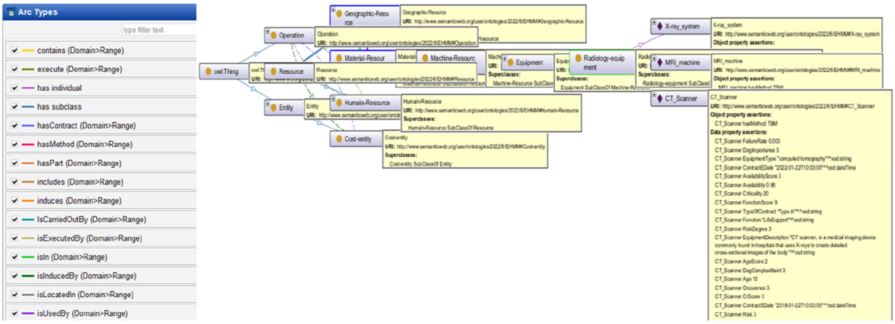
Source(s): Table created by authors

Table 13.
SQWRL rules for listing equipment criticality, assigned maintenance strategies, and selected contract types

from internal maintenance reports, ensuring the creation of a representative and relevant dataset, covering various scenarios, for testing and refinement purposes.

The process of implementing the model involves enriching the domain knowledge, which is modeled by the ontology and expressed in OWL through case-specific data entry. Subsequently, new facts are inferred to the knowledge base from the model through the integrated SWRL rules, while SQWRL queries are employed to retrieve decision-support recommendations and other pertinent information for management purposes. In this context, domain knowledge is represented by concepts (or classes), relations and attributes, as detailed in Section 2.1. Figure 9 illustrates an example introducing the subclasses of the “Equipment” class, with the “Radiology-equipment” subclass highlighted alongside its relations, while Figure 10 presents the associated domain knowledge expressed in OWL language.

Figure 11 highlights the “CT_Scanner” as an instance of the “Radiology-equipment” subclass and displays its properties, which are divided into data properties and object properties.



Source(s): Figure created by authors

Figure 9. Preview of the instances of the “Radiology-equipment” subclass and the associated relations

```
Prefix: : http://www.semanticweb.org/user/ontologies/2022/6/EHMM#
Prefix: owl: http://www.w3.org/2002/07/owl#
Prefix: rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>Prefix: rdfs: http://www.w3.org/2000/01/rdf-schema#
Prefix: xml: http://www.w3.org/XML/1998/namespace
Prefix: xsd: <http://www.w3.org/2001/XMLSchema#>
<owl:Class rdf:about="http://www.owl-ontologies.com/EHMM.owl#Radiology-equipment">
<rdfs:subClassOf rdf:resource="http://www.owl-ontologies.com/EHMM.owl#Equipement"/>
<owl:Individual>
        <owl: Individual: CT_Scanner   Annotations:     rdfs:comment "The X-ray system in the
         uses electromagnetic radiation to produce images of internal body structures, allowing doctors to
        diagnose and treat various medical conditions..“ </owl:Individual>
<owl:Individual>
        <owl: Individual: X-ray_System   Annotations:     rdfs:comment "CT Scanners: Computed
        Tomography (CT) scanners are another critical diagnostic tool in modern
        hospitals."</owl:Individual>
<owl:Individual>
        <owl: Individual: MRI_machine   Annotations:     rdfs:comment "The MRI machine uses a
        strong magnetic field and radio waves to generate detailed images of soft tissues, organs, and
        bones, providing valuable diagnostic information to medical professionals.."</owl:Individual>
```

Source(s): Figure created by authors

Figure 10. Radiology-equipment associated domain knowledge in OWL language

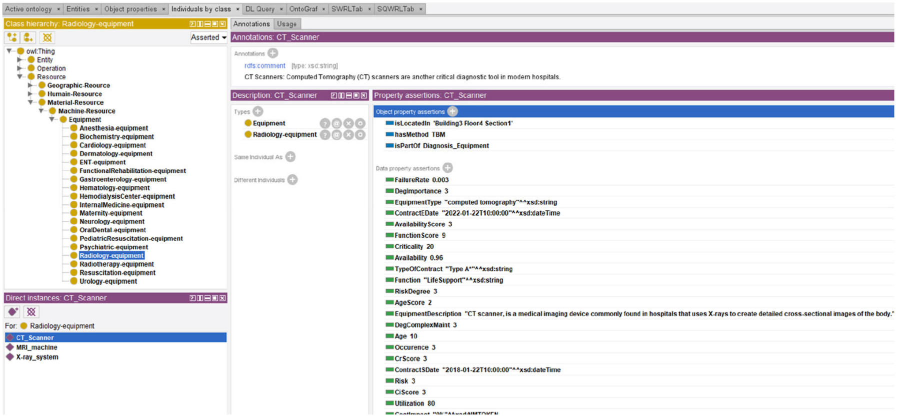


Figure 11.
Preview of the properties of the instance “CT_Scanner”

Source(s): Figure created by authors

The object property assertions in Figure 11 reveal the equipment relations of which its maintenance strategy is part (defined by the relation “has method”), while the data property assertions regroup the equipment specifications (age, function, cost impact, etc.) along with its respective evaluation scores (criticality, function score [FS], importance degree score, etc.) calculated using the SWRL rules presented in the previous section. For example, the FS is calculated using the equipment function specification as input, as indicated by the SWRL rule 2.1 (Figure 12).

The facts inferred from the model by the SWRL rules constitute together the outcome of the integrated decision-support modules, which imply the assessment of the equipment criticality, in addition to the assignment of maintenance strategies and the contracting policies, accordingly. The relevant results can be retrieved for all the equipment using SQWRL queries. Figure 13 demonstrates an example in which the calculated equipment criticality values are retrieved along with the assigned maintenance strategies, using SQWRL rule 4.2.

By customizing the SQWRL queries, it is possible to retrieve other useful information as well. Figure 14 demonstrates an example allowing to retrieve the equipment listed according to several attributes including criticality, age, maintenance method (strategy) and the type of applicable contract along with its validity period.

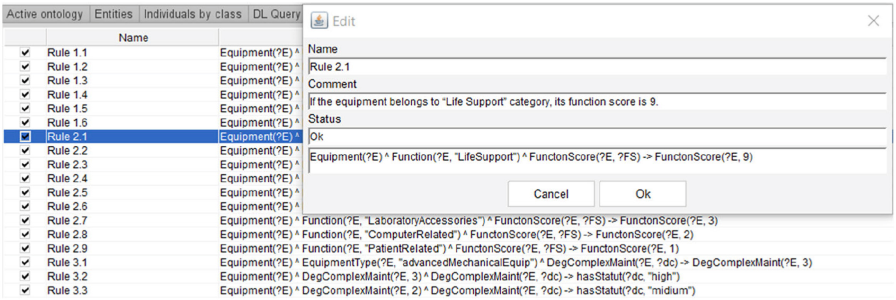
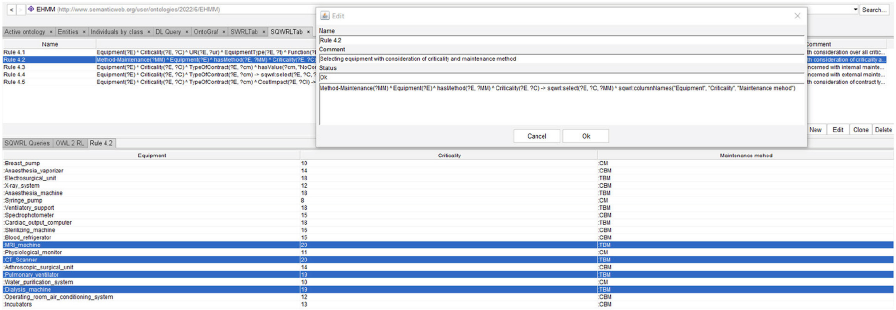


Figure 12.
Preview of the SWRL rules allowing to calculate the function score with rule 2.1 highlighted

Source(s): Figure created by authors

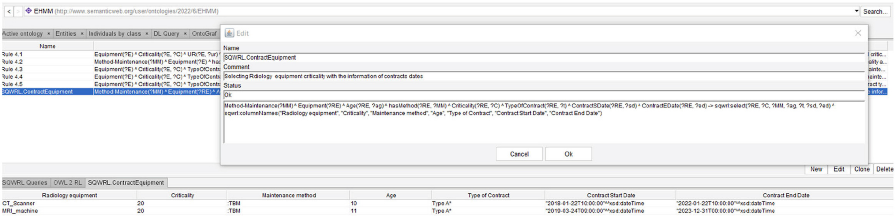
4.2 Integrated decision-support outcome

As previously described in section 2.2, the integrated decision-support modules of the system cover criticality assessment, maintenance strategies assignment and maintenance contracting policy selection. The obtained results in this context regarding the selected set of equipment are retrieved using the SQWRL queries described in Table 13 and are synthesized in Figure 15.



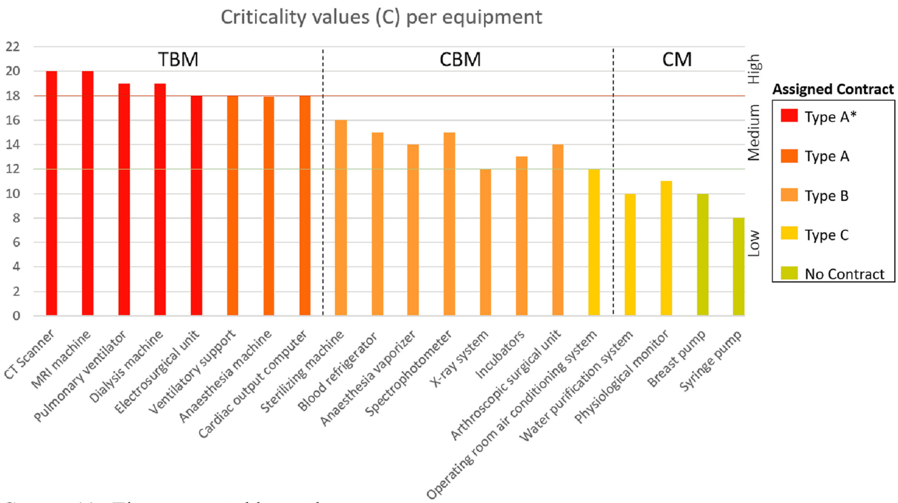
Source(s): Figure created by authors

Figure 13. Retrieval of criticality values and maintenance strategies per equipment, using SQWRL rule 4.2



Source(s): Figure created by authors

Figure 14. Retrieval of other useful information by customizing the SQWRL rule attributes



Source(s): Figure created by authors

Figure 15. Obtained decision-support results

Figure 15 shows that 40% of the processed equipment is highly critical and should therefore receive a TBM strategy, while another 40% is classified as having medium criticality and should receive a CBM strategy. The remaining 20% is considered to have low criticality and should therefore undergo CM. In terms of maintenance contracting policy selection, the results indicate that 90% of the equipment should be externally maintained, with 25% of the equipment under contract type A*, 35% under contract type B and 15% under each of contract types A and C.

4.3 Validation of the system

To validate the system, multiple steps are taken. First, a reasoner-based evaluation is conducted to verify the consistency of the internal categories and the SWRL rules and to ensure that there are no conflicts among them. Additionally, the SQWRL queries are checked to confirm that the attributes are correctly defined and that relevant information can be retrieved. The Hermit reasoning plugin integrated into Protégé is used to automate this process and no errors are found. The next step is an expert-based validation, which involves communicating with hospital professionals who provide the knowledge required to design the system, including maintenance and biomedical engineers, doctors, paramedics, executives and department managers. Their feedback confirmed that the system meets their requirements and is satisfactory. Additionally, they suggested further avenues to develop its potential, which could be the subject of future work.

5. Conclusion

The development of an ontology-driven maintenance management system for medical equipment presents significant potential in enhancing the maintenance processes of healthcare facilities. The system's ability to assess equipment criticality and assign maintenance strategies and contracting policies has been shown to be effective through a real-life case study. The system's advantages, such as improved decision support, knowledge sharing and seamless interoperability, underscore its added value to the medical field. The validation process ensures that the system is accurate, consistent and effective in meeting the needs of hospital staff.

It is essential to highlight that various elements of the presented model, including ontology concepts, subclasses, relations and attributes, have been integrated but are currently not employed within its decision-support workflow. These components have been included in the knowledge base to allow using the system as an information portal and have the potential to be leveraged in the future to provide decision support at new levels, whether within the maintenance function (e.g., maintenance staff and inventory management) or the broader realm of overall facility management (e.g., patients management and medical dispensation delivery). This feature provides the model with significant potential for further development.

However, as the model evolves, there might be a need to address certain limitations by integrating advanced techniques. For example, incorporating Blockchain can enhance security, trust and data integrity, which is particularly beneficial for maintaining confidentiality in aspects like contracts and patient data. Simultaneously, the IoT can provide real-time monitoring and automation for proactive management. The synergistic use of these technologies can streamline supply chain processes, automate procurement and enhance resource allocation, while also fostering decentralized collaboration and overall interoperability. Additionally, integrating multicriteria decision-making techniques can significantly improve decision support through a more rigorous data-processing approach.

Ultimately, this study demonstrates the potential of ontology-driven maintenance management systems to optimize maintenance processes and enhance the quality of patient care in healthcare facilities. Further improvements can make it even more effective and valuable in the healthcare industry.

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