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An approach of ontology and knowledge base for railway maintenance

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ABSTRACT

Maintenance methods have become automated and innovative, especially with the transition to maintenance 4.0. However, social issues such as coronavirus disease of 2019 (COVID-19) and the war in Ukraine have caused significant departures of maintenance experts, resulting in the loss of enormous know-how. As part of this work, we will propose a solution by exploring the knowledge and expertise of these experts for the purpose of sharing and conservation. In this perspective, we have built a knowledge base based on experience and feedback. The proposed method illustrates a case study based on the single excitation configuration interaction (SECI) method to optimally capture the explicit and tacit knowledge of each technician, as well as the theoretical basis, the model of Nonaka and Takeuchi.

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1. INTRODUCTION

The coronavirus disease of 2019 (COVID-19) crisis has demonstrated the importance of knowledge sharing for business resilience in general. According to the World Economic Forum. There is a need for businesses to make their businesses more resilient to future disasters and pandemics [1]. The main lesson we learned from COVID-19 is to know how to rely on your own strengths as a key driver of resilience. Today, digital transformation has moved from a simple trend to a paradigm that manipulates the accelerated and irrevocable changes that the whole world is experiencing [2]. In railway maintenance, we talk about predictive maintenance or maintenance 4.0, which anticipates the deterioration of installation performance. Depending on the technology, existing solutions can detect signs of wear more or less early, such as ultrasound, vibration analysis, oil analysis, and temperature control [3]. To take full advantage of these solutions, it is necessary to analyze the measurements obtained and make accurate diagnoses to avoid unnecessary costs associated with stopping and disassembling/reassembling the machine, which later proves to be unnecessary. However, this diagnosis comes at a cost, as it is often no longer within the purview of a general maintenance technician or engineer but requires the intervention of an expert with a specific approach [4]. Over the past decade, several serious rail accidents have occurred. For example, the China-Yongwen railway operating accident occurred in July 2011, killing 40 and injuring 172 [5]. In December 2015, an Amtrak passenger train derailed in Philadelphia, killing 8 and injuring 185 [6]. Less than a year later, the Santiago de Compostel train derailment in Spain occurred and left 78 dead and 145 injured [7]. The railway company experienced a significant fluctuation in staff and the departure of these trade experts for different reasons as shown Figure 1.

The company has to find an urgent answer to the following question: How can a company face this huge loss of its knowledge and know-how without losing the efficiency of the maintenance activity? Good governance of the rolling stock and railway equipment maintenance process, staff training as well as exploration and understanding of past accidents are the fundamental tools to prevent railway operating accidents [8], [9]. Valuable knowledge contributing to accident prevention can be captured from the understanding of past railway operating accidents [10]. Taking advantage of the rapid progress of data analysis and networking technologies, the company has set up a capitalization project that aims to preserve and secure this know-how heritage [11]. This information must be put into its evolutionary context and thus become knowledge [12]. In this perspective, our work attempts to set up a resilience plan for the maintenance activity considered the most critical in a railway company, while guaranteeing transparency and access to information for all. To do this, we have proposed to set up a knowledge base; this base will make it possible to take proactive decisions, which contribute to the improvement of productivity. The added value or contribution of this work comes from the criticality and complexity of the activity dealt with. In fact, in a railway company, more than 50% of the staff exercises a job related to safety, directly or indirectly; more particularly the maintenance managers who perform their duties in an environment subject to strict safety requirements. This work aims to provide the business with the ability to prepare and adapt to changing conditions and to withstand and recover quickly from disruptions.

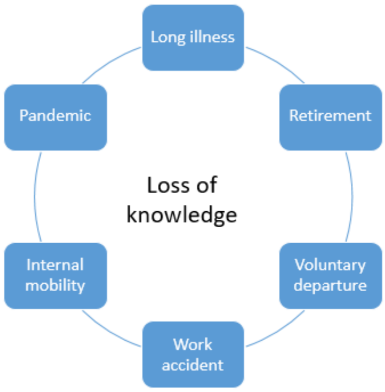

Figure 1. Example of reasons for leaving

2. THE PROPOSED METHOD

2.1. The concepts related to knowledge management (KM)

We have two types of knowledge: i) explicit knowledge is knowledge that can be memorized and retrieved consciously and then expressed in formal or systematic language [13], [14] and ii) implicit knowledge is non-expressible and is that of which the individual is not aware [12]. This knowledge includes innate or acquired skills, expertise, and experience. If that individual leaves, you immediately lose their tacit knowledge, as it is based on their individual experience. They are generally difficult to formalize as opposed to explicit knowledge. In a business, tacit knowledge can be assimilated into intellectual capital. According to Nonaka and Takeuchi [13], [14], [9], there are four modes of knowledge conversion from one category to another as shown in Figure 2.

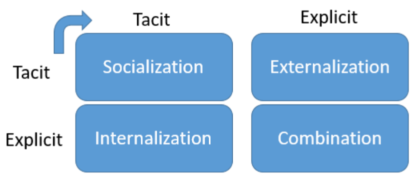

Figure 2. The single excitation configuration interaction (SECI) spiral of knowledge creation (Nonaka and Takeuchi) [13]

The modes of knowledge conversion in the same category or to another are:

– Socialization: Which represents the mode of transition from one state to another of tacit knowledge [15]. This is achieved for example, when sharing experiences between human actors through the observation and reproduction of practices such as maintenance practices.
– Exteriorization: This operation consists of making tacit knowledge explicit through modeling or the use of analogies, metaphors, and/or hypotheses.
– Internalization: Consists of assimilating explicit knowledge by the individual to the point of becoming an automatism [15].
– Combination: It is the passage from explicit knowledge to explicit knowledge. For example, when new knowledge is revealed following explicit exchanges of knowledge between several individuals with a common language.

2.2. Knowledge capitalization processes

KM processes are conceptualized to define a sustainable methodological framework that allows the capitalization and transmission of knowledge and know-how over time [9]. To this need for temporal durability [16]. The standard KM process consists of the summary of four phases to be carried out continuously in a determined order: identity, preserve, enhance, and update this knowledge as shown in Figure 3.

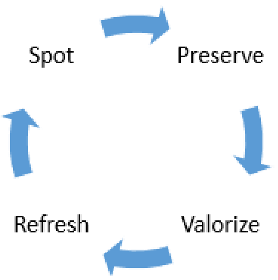

Figure 3. KM process [17]

– Identify: The first phase of the KM process focuses on identifying the crucial knowledge necessary for the decision-making process and the conduct of activities [18]. It consists in identifying, locating, characterizing, and prioritizing the knowledge and know-how of experts [17].
– Preserve: It consists in acquiring knowledge and know-how from their carriers (experts). Then, this knowledge must be modeled, formalized, and stored in documents, graphs, or functional procedures [17].
– Valuing: This consists of valuing the knowledge and know-how identified and capitalized in the two previous phases. It allows for making capitalized knowledge accessible to all actors in the organization through sharing and dissemination of media such as operating procedures, diagrams, and information systems [17].
– Update: Finally, to ensure the adaptation of knowledge, know-how as well as models and operating protocols associated with the continuous changes in the environment, it is important to update them by evaluating their relevance, than by enriching them with new knowledge [17], [18].

2.3. Ontology a knowledge base

Ontology is the basis of what is called knowledge representation [19], [20]. This field was born by researchers to represent various knowledge of the world so that they could be used by computers, so they could reason about this knowledge [20]. This knowledge is expressed in the form of symbols to which we give a "semantic" (a meaning). Knowledge bases are made up of [19]:

– An ontology: A collection of classes and relations (that we will call property for the same reasons as a concept) between these classes.
– Rules: An expression of constraints on the properties and classes of the ontology.
– Facts: Instances of ontology It includes machine-interpreted definitions of basic concepts in the domain and relations among them [19], [20]. The semantics of the data is described by ontologies with languages designed to provide a formal description of concepts, terms, or relations of any domain. These languages are resource description framework schema (RDFS) and web ontology language (OWL) [19].

3. RESEARCH METHOD

A knowledge generation strategy refers to a systematic approach or plans that an organization uses to create new knowledge or information. This strategy involves identifying a problem, gathering data, analyzing the data, synthesizing information, and drawing conclusions. In this section of our article, we started with the approaches used in industrial maintenance in general before focusing on the railway maintenance domain.

3.1. Knowledge generation strategy for maintenance

Firstly, we have identified a multitude of articles that focus on the use of knowledge bases in the maintenance domain. Previous qualitative surveys [21], showed the importance of the factors that allow the influence of KM in the engineering of the maintenance, its obstacles, and facilitators. Knowledge transmission and management mechanisms are mainly created by maintenance activities. However, they are little studied due to the difficulty of capturing them because they belong to tacit knowledge acquired through the experience of maintenance staff. These professionals are highly qualified and are accustomed to solving technical problems even under pressure. The loss of these professionals also means the loss of an important asset of the company. Xur *et al.* [22] designed a fault diagnosis system for loaders based on ontology. This system aims to help users find the fault causes, location, and maintenance measures of the loader within a reasonable time. Ontologies are used to model loader information and describe related errors. This work uses a condition-based reasoning (CBR) approach to diagnose loader failures by finding similar corresponding situations in the past. If no corresponding case is found, CBR fails, and semantic web rule language (SWRL)-based rule reasoning (RBR) methods are recommended for error diagnosis. Next, the author's study based on qualitative research and technician's surveys [23] pushed to demonstrate that an effective level of tacit knowledge is favorable in this subject. They focused on the difference between the perception of explicit knowledge, and knowledge acquired or tacit by maintenance technicians. So, due to the departure of a collaborator, a piece of important strategic knowledge is lost, it is a return of experience and know-how that are volatile and negatively impact the company. Always in the same vision, in [24] they studied the intellectual structure and the tendencies of knowledge management in industry 4.0. The bibliometric analysis carried out allowed us to lay the foundations to determine how knowledge management and its practices evolve in the digital age, thus providing researchers with an adequate systematization of knowledge relating to this field of research. The results of this research suggest that practitioners in the field of knowledge management must take into account, understand, and integrate the different dimensions of industry 4.0 advances in their organizations, thereby mitigating the negative effects on organizational performance.

3.2. Knowledge generation strategy in railway

Concerning the railway, several articles have dealt with aspects related to this field. Chiach *et al.* [25] proposed a prognostic methodology applied to the particular problem of railway track geometry deterioration. A knowledge-based prognostics approach is developed by fusing online data for track settlement with a physics-based model for track degradation within a filtering-based prognostics algorithm. The results of the proposed methodology show that is able to provide accurate predictions of the remaining useful life of the system after a model-training period of about 10% of the process lifespan. Taheri *et al.* [26] have proposed a new knowledge-based system for the evaluation of railway fastening using an automatic image system. For this purpose, imaging data were first collected. Next, using an expert system, the location of the fastening system was detected and then two indices were presented; one for evaluation of single bolts, and the other one for fastening system assessment. Experimental results show the efficiency of the proposed system in automatic judgment for railway direct fastening. Furthermore, it has been reported that a novel knowledge-based system for predictive maintenance in industry 4.0 (KSPMI). KSPMI is developed based on a novel hybrid approach that leverages both statistical and symbolic artificial intelligence (AI) technologies [27]. The hybrid approach involves using statistical AI technologies such as machine learning and chronicles to extract machine degradation models from industrial data. This hybrid approach uses SWRL rules generated from chronicle patterns together with domain ontologies to perform ontology reasoning, which enables the automatic detection of machinery anomalies and the prediction of future events' occurrence. All of the aforementioned works use knowledge bases for the improvement and optimization of maintenance operations. However, none of these works satisfies all the requirements we have identified: the fluctuation of staff and the departure of experts. Indeed, in the introduction, we raised the issue of the departure of experts, the component of versatility, and the use of subcontracting that hinders the changeover or the transition to maintenance 4.0. The 4.0 maintenance has a cost since it is generally no longer within the reach of a technician or a general maintenance engineer but requires the intervention of an expert with a specific methodology as well as investments in equipment (sensors, data collection devices, ...) and software. Our contribution by the implementation of a knowledge base based on the experience and know-how of the oldest and most experienced in the field (first in a pilot site and then generalized to the entire railway network) will allow, among other things: i) limit the loss of knowledge linked to an insufficient transfer of knowledge between old and new generations and ii) improve the capacity of analysis, diagnosis, and problem-solving by too generalist profiles.

4. RESULTS AND DISCUSSION

4.1. Methodology

4.1.1. Extraction of knowledge from maintenance technicians

Our approach is divided into three bricks as shown in Figure 4, the first consists of collecting data by questioning the maintenance technicians of the pilot site through a survey. Each technician shared the basic skills; that every technician must have to carry out these missions; as well as his tacit knowledge concerning the types of maintenance carried out at the pilot site. Explicit knowledge is converted into new explicit knowledge by a combination of knowledge, and the previous tacit knowledge is then converted into explicit knowledge in the form of the quiz result. The second type involves extracting the history of the data recorded in the computer-aided maintenance management system (CMMS) or instructions in the procedures relating to the maintenance operations carried out by these technicians on their site. The third one consists of data comparison and validation by a senior expert. This helps to merge them into a single complete piece of information, which allows for the construction of our knowledge base. Our study will be carried out in a pilot establishment chosen based on the following criteria: number of alerts affected, the seriousness of these reports, type of equipment, and reactivity of resources attached to this site. The pilot site is made up of 110 people with the following divisions presented in Table 1.

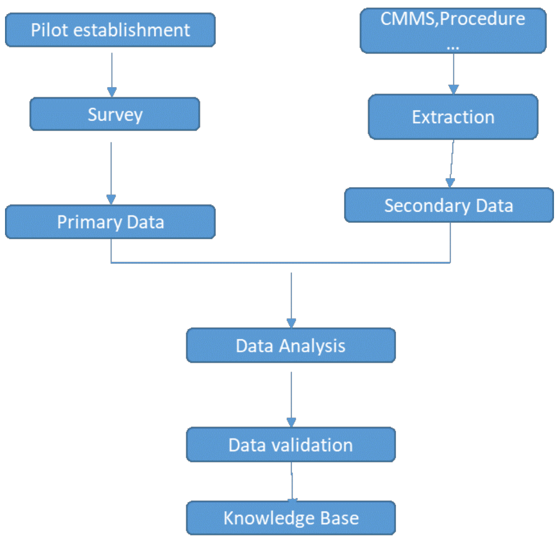

Figure 4. Knowledge generation approach

Table 1. The target population

Function	Experience				
	¡=5 years	5¡ and ¡=10 years	10¡ and ¡=20 years	¿=20 years	surveys’ total
Manager	1	0	2	1	4
Visitor chief	1	0	0	7	8
Operator	1	2	5	17	25
Technician	25	9	7	32	72
Total:	30	11	14	57	110

4.1.2. The survey

This survey is used to evaluate an individual's abilities and expertise in railway maintenance. This tool can provide valuable insights into an individual's strengths and weaknesses, which can help them improve their performance in the future. The survey questions is designed to assess the specific abilities and expertise we want to evaluate. The questions are clear, concise, and easy to understand. We have use both closed-ended and open-ended questions. The survey is divided into two parts.

a. Skills grid

The survey as shown in Figure 5 will allow the collection of explicit knowledge. On the pilot site, they have 11 teams for different specialties: mechanical, electrical, electronic, brake, air conditioning, pneumatic, automatism, adjustment, bogie, comfort, and roofing. Evaluation is made according to 5 levels: i) beginner: knowledge of the specialty; ii) intermediate: less than one year in the specialty; iii) confirmed: at least one accreditation or one year in the specialty; iv) mastery: at least two accreditation or two years in the specialty, and v) expert: at least three accreditation or three years in the specialty.

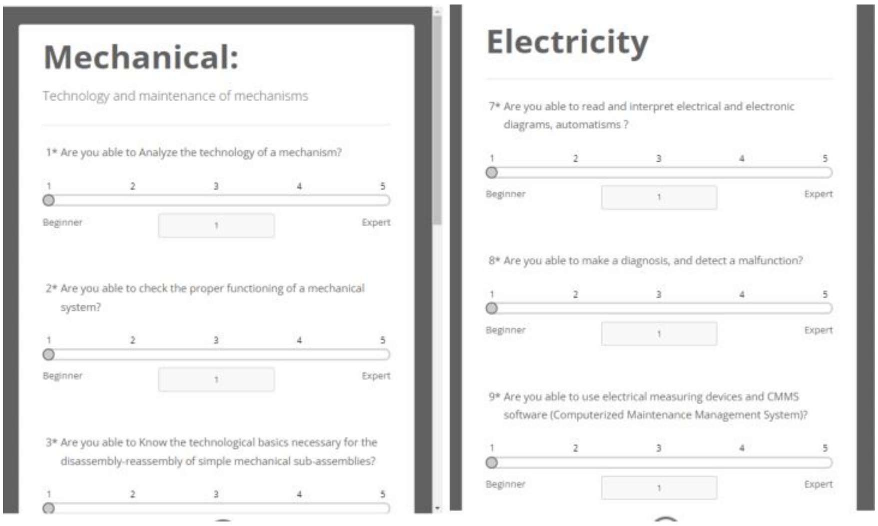

Figure 5. Survey format, among maintenance technicians

b. Knowledge grid

Tacit knowledge builds on explicit knowledge, which is the step-by-step information an employee needs to complete a task. From there, they gained experience performing that task and built their tacit knowledge from the practical application [28]. After performing the task many times over the years, the person gains tacit knowledge, which is difficult to explain to others in a simple document or over the phone. We asked questions based on the top 20 most frequent and most impacting failures; for each failure, we tried to collect as much knowledge as possible from the technicians by the survey as shown in Figure 6.

- What is the level of severity you propose for this failure?
- Is it a repetitive failure?
- Why do you think this failure appears in the Top 20?
- Can you identify the symptoms of this failure?
- Can you determine the component that presents this symptom?
- Do you know the impact of this failure on the component?
- What is the nature of the cause of this failure?
- What are the measures to apply to solve this failure?
- Is there a procedure for the resolution of this failure?
- Do you consider the existing documentation sufficient to ensure the complete treatment of this failure?
- Do you have other proposals than the procedure for the resolution of this type of failure?

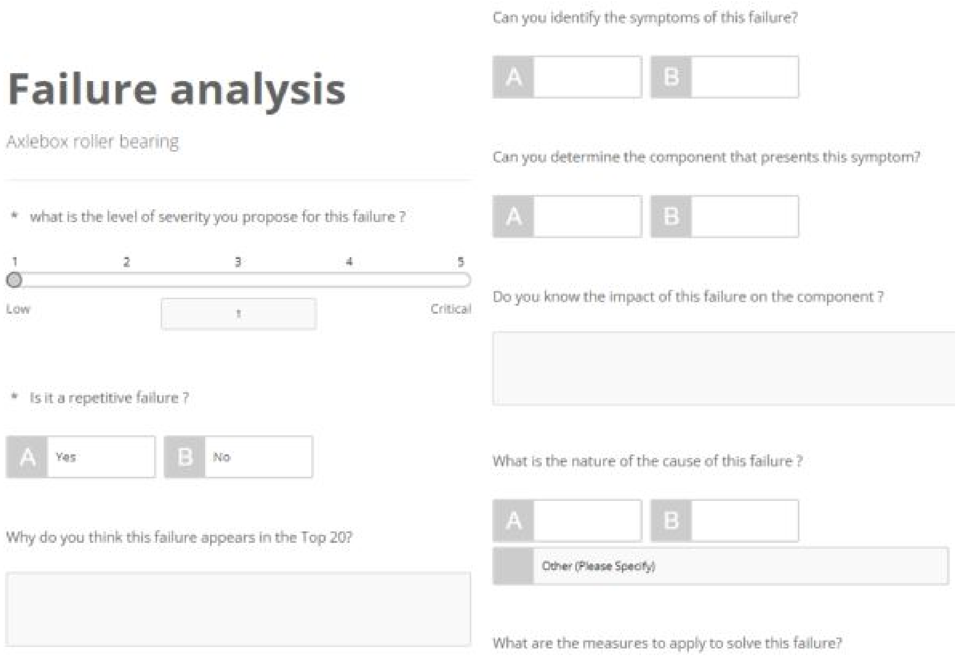

Figure 6. Survey format for tacit knowledge

4.1.3. Analysis and validation of results

Firstly, we need to do some transformations on our dataset, to ensure the confidentiality of our data, so it is imperative to anonymous the data. It is necessary to proceed to the generalization that consists in modifying the scale of the attributes of the data sets, or their order of magnitude, to ensure that they are common to a set of people. Based on the target population, the following Table 2 presents the number of returned questionnaires according to the function and the number of years of experience of the maintainers. Sometimes, an interview was necessary to confirm or validate the information.

Table 2. Survey population based on function and years of experience

Function	Experience				
	¡=5 years	5¡ and ¡=10 years	10¡ and ¡=20 years	¿=20 years	surveys' total
Manager	1	0	1	1	3
Visitor chief	1	0	0	5	6
Operator	1	1	4	9	15
Technician	15	5	6	17	43
Total:	18	6	11	32	67

Since always, the need to reduce their operating costs as much as possible. Companies are increasingly resorting to subcontracting or temporary work and are looking for more generalist and versatile profiles of maintenance technicians and engineers [19]. This has been proven by our distribution of expertise by the number of years for all specialties as shown in Figure 7 of our pilot site. As shown in Figure 7, for technicians with less than 5 years of experience, it is quite natural that the notion of expertise does not exist as well as the mastery level where the number is minimal. For those who have an experience of between 5 and 10 years, we notice a very important level of confirmed considering the total number of technicians in this category. On the other hand, from 10 years of experience, the level of expertise is seen as well as the mastery level; we also notice the absence of lower levels.

What was surprising for the 4th category, was the Beginner level, which was reported by many technicians given their expertise in one or two specialties at most and not mastering the rest. Two very important points were highlighted: i) the expertise in a specific specialty exists only in technicians over 20 years and ii) the notion of versatility is very present in technicians with more than 5 years of experience.

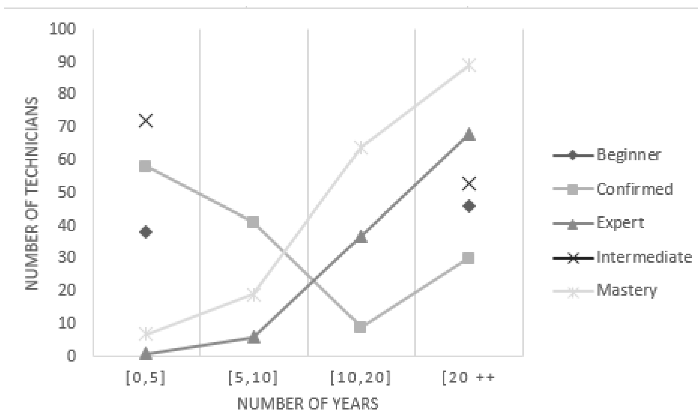

Figure 7. Distribution of expertise by number of years for all specialties

Figure 8 confirms the notion of versatility among the different technicians at the pilot site. For the validation phase, knowledge is created according to the following rules: i) the same knowledge has been confirmed by at least 3 technicians without being detected in the CMMS and ii) the knowledge has been confirmed by a technician and exists in the CMMS Table 3 shows an example of a combination process. It is known that the combined process is performed by comparing each technician's response, in addition to extracting from the CMMS. After processing and validating all the responses to the questionnaires, the next step is to build our knowledge base.

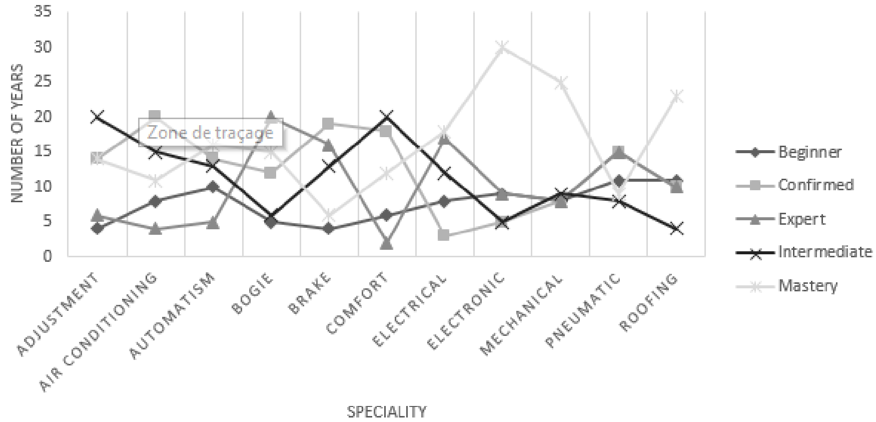

Figure 8. Distribution of expertise by specialties

Table 3. Example of failure analysis and validation

Technician	Failure	Component	Symptom	Cause	Solution
Technician 1	pantograph failure	Pantograph	failure to climb	air leak	Flexible air supply replacement
Technician 2	pantograph failure	Pantograph	failure to climb	pre-charge circuit failure	Replacement of 1KCF contactor fingers
Technician 3	pantograph failure	Pantograph	Peeling off	Low tension of the ascent springs	Pantograph setting
Technician 4	pantograph failure	Pantograph	Peeling off	Low tension of the ascent springs	Change of springs
Technician 5	pantograph failure	Pantograph	Peeling off	Low tension of the ascent springs	Pantograph setting
CMMS	pantograph failure	Pantograph	failure to climb	MH pantograph does not rise even with energized solenoid valve no audible leak	Flexible replacement

4.1.4. The challenges of the approach

During our quest for the collection of knowledge, we faced a set of challenges. Indeed, the main challenge was the deliberate concealment of knowledge, this is not surprising, especially considering the population targeted by this work. Indeed, technicians are afraid of devaluing their own importance in the organization if they share their knowledge. Some do not see the interest and the advantages of sharing knowledge, if we add the problems of internal communication and organizational tensions, all these constraints upset the established rules of open sharing of knowledge. On the other hand, the repetition of operations leads to a large proportion of common knowledge and a drying up of creativity. In certain situations (critical incidents and traffic blockages), technicians must make decisions quickly and do not have time to build a portfolio of knowledge. In this case, it is easy to tap into common knowledge without contributing to it.

4.2. Building ontology (knowledge base)

4.2.1. Conception

For the conception of our ontology, we adopted the W3C [29] model. The goal is to provide a standardized, machine-readable representation of knowledge that can be shared, reused, and integrated across different applications and systems on the web. The steps involved in creating an ontology in the context of W3C are:
Step 1. Determine the domain and scope of the ontology

To determine the domain and scope of the ontology, we schematized a list of questions that the knowledge base based on this ontology should be able to answer [29], [30]. Examples of questions that our knowledge base should be able to answer:

- What is the domain that the ontology will cover?
- For what purpose are we going to use this ontology?
- What types of questions should the information in the ontology answer? Then, for the skills component, we established a series of questions that our ontology must be able to answer:
- What characteristics should I consider when choosing a technician?
- Who is the best technician in establishment Y in terms of responsiveness?
- What is the most expensive maintenance operation at establishment Y?
- What is the recurring cause for failure X?
- Solution X is still valid for failure Y?
- What is the impact of failure Y on component Z?

Judging by this list of questions, the ontology must include information on the characteristics of the rolling stock and its components; the types and characteristics of the maintenance operations carried out, and finally, the human resources that operate in the different maintenance centers.
Step 2. Reuse already existing ontologies

Reusing existing ontologies [29], [30], refers to using ontologies that have already been developed and are publicly available, rather than creating a new ontology from scratch. In our case, there is no ontology, that meets the specific requirements of our use case.
Step 3. List the important terms of the ontology

This step consists in defining the list of all existing terms since it would be nice to be able to make statements about a subject without worrying about the overlap between the classes that the terms represent, the relationships between the terms, or the properties that the terms represent [29], [30]. These terms form the building blocks of an ontology and are used to define the concepts, categories, and relationships in a particular domain.
Step 4. Define classes and class hierarchy

In this step, we define the most important classes first, then generalize and specialize them appropriately as we design [29], [30]. This approach is the easiest to follow. We organize classes in a hierarchical taxonomy to ask whether by being an instance of one class, the object will necessarily be an instance of another class.
Step 5. Set ontology properties

Each class has properties. The properties of a class are attached to this class. In general, several types of properties are found in a knowledge base [29], [30]: intrinsic properties, extrinsic properties, and relationships (what are relationships between individual members of the class). For the development, we used Protégé

[31]. Protégé is a free and open-source ontology editor, one of the most widely used ontology development tools. It was developed at Stanford University. From the previous phase, we identified two important ontologies, namely rolling stock, and failure. The ontology would allow for a structured and organized representation of knowledge about rolling stock, enabling more efficient storage, retrieval, and analysis of information.

4.2.2. The rolling stock ontology

The rolling stock ontology as shown in Figure 9 refers to machines that move on a railway track, including trains and locomotives. A rolling stock ontology describes the various types of rolling stock, their properties and attributes, and the relationships between them. This includes information about the manufacturer, model, year of production, technical specifications, and historical information. This will allow us to link maintenance operations and failures to specific machine components when and where they occur:

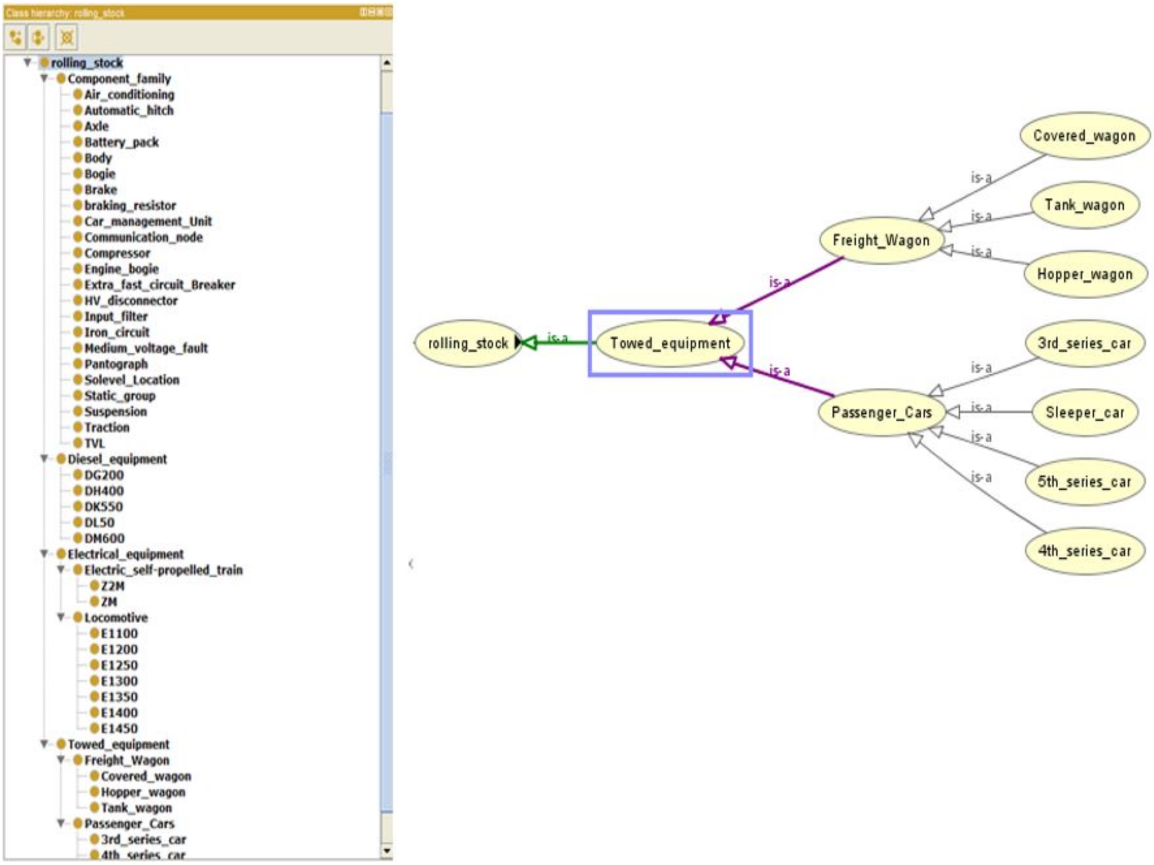

Figure 9. The snapshot of rolling stock ontology

4.2.3. The failure ontology

The failure ontology as shown in Figure 10 describes various concepts related to the failure of rolling stock, such as types of failures (mechanical and electrical), causes of failures (wear and tear and manufacturing defects), and consequences of failures (delays and maintenance costs). The relationships between these concepts are also represented, such as how a specific type of failure may lead to certain consequences, or how different entities are responsible for addressing different types of failures. The ontology can then be used for various purposes, such as reasoning about the causes and effects of failures, and supporting decision-making processes related to the management of rolling stock.

4.2.4. Property definition

When we develop an ontology, two types of properties should be identified, data properties and object properties. Object properties define relationships between classes. In our case, the base ontology specifies the relationship between all other ontologies, so an example of object properties is shown in Figure 11. This article omits other object properties and data properties.

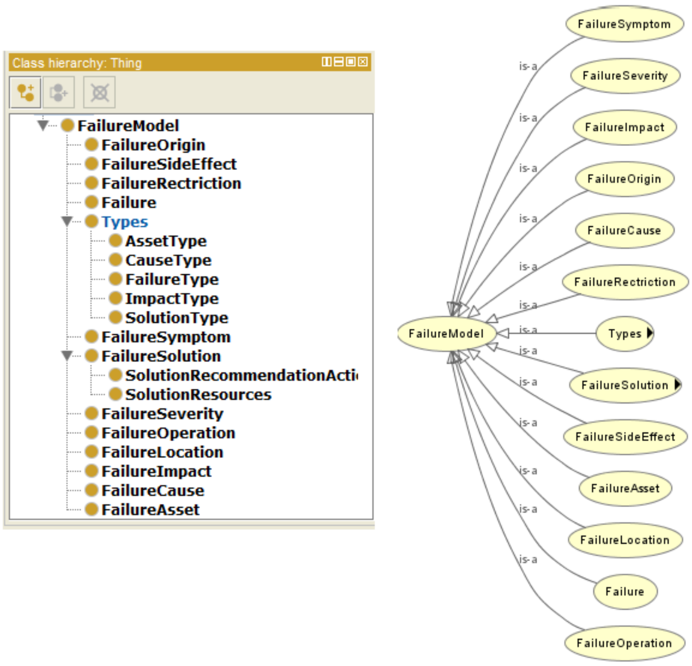

Figure 10. Extract snapshot of failure ontology

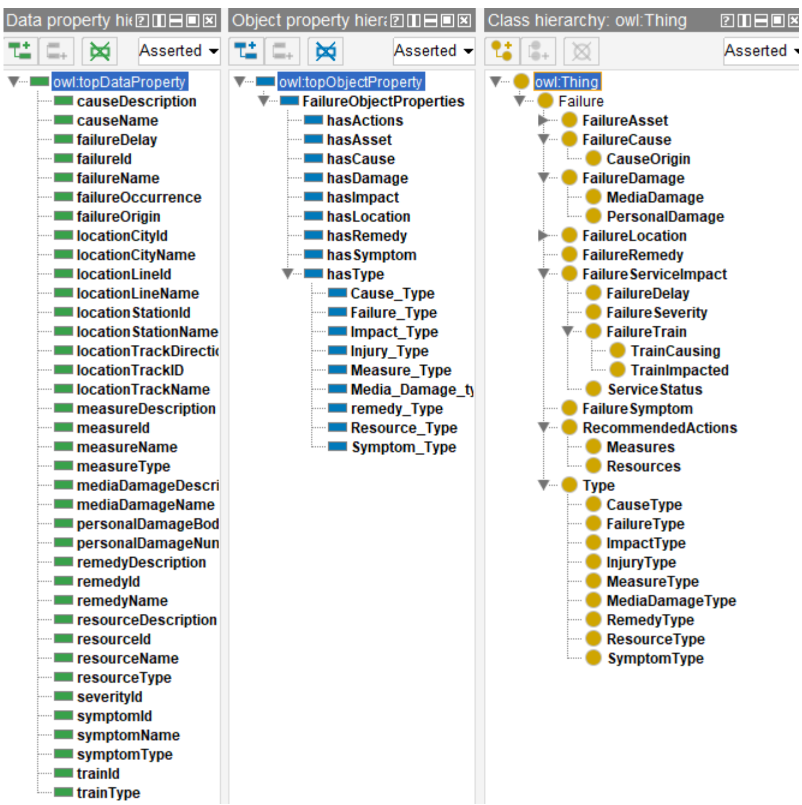

Figure 11. Example of object properties

4.3. Synthesis

Our ontology has been built, with the inclusion of 341 classes and 80 properties as shown in Table 4, the ontology results provide a better understanding of the structure and organization of rolling stock and can help in the development of new insights and ideas for failure handling. By understanding the structure and organization of the different components and systems in the rolling stock, we can identify potential points of failure and develop strategies to mitigate them:

Table 4. Results

Ontology	Classes	Properties	individuals
Rolling stock	105	23	3,000
Failure	236	57	3,500
Total	341	80	6,500

These ontologies for railway maintenance can provide several benefits for the site described in paragraph 4.1, including:

- Better decision making: Rolling stock ontology provides a clear and comprehensive understanding of the different types of railway assets, their properties, and their relationships. This can support more informed decision-making by providing a more complete picture of the rolling stock and its components.
- Improved data management: Rolling stock ontology provides a structured and standardized representation of the data and knowledge related to rolling stock. This can help to improve data consistency, making it easier to manage, analyze, and share data across different departments and organizations.
- Increased efficiency: Failure ontology support workflows, by reducing the time and effort required for manual data entry and retrieval. This can help to improve the overall efficiency of railway maintenance processes.

Overall, an ontology for railway maintenance help to improve the efficiency, quality, and consistency of maintenance processes, and support more informed decision-making. By generalizing the scope of a rolling stock ontology, it becomes possible to create a shared understanding of rolling stock assets that can be used across different organizations and applications. This can lead to more efficient and effective management and analysis of rolling stock assets.

4.4. Recommendations

Sharing knowledge starts with listening before sharing. Preliminary listening is a requirement, regardless of whether the sharing is done with internal or external actors. So that the sharing of knowledge can succeed, it is essential to know the audience and their specific challenges by listening before sharing. After the success of our prototype and the validation of the data by the experts, we established a list of recommendations to be able to generalize this work to all the maintenance centers: In the immediate future, the implementation of an additional module to existing CMMS for the collection of information directly during the processing of failures, indeed, after the drafting of a report, the technicians will fill out an additional form to enter their feedback from the maintenance operations carried out, its opinion and the expected effectiveness of these actions. Adding general automatic notifications for the publicity of the technicians' achievements will show that knowledge sharing and learning are priorities for the program. In the medium term, the establishment of a reward system will highlight the value given to sharing and learning knowledge. The system can be used to spread knowledge-sharing practices across the organization or program by recognizing the work of individuals and teams. Another proposal is that an award system can be created whereby any member of staff can nominate a colleague for recognition of excellence in knowledge sharing.

5. CONCLUSION

We have proposed a complete process based on the SECI method for the optimal collection of explicit and tacit knowledge from each technician. In this process, we relied heavily on theoretical bases, namely the Nonaka and Takeuchi models. The proposed strategy is to identify, analyze and integrate this knowledge into the corporate knowledge base, which has been developed as an ontology. The main challenges encountered during this work were: the resistance of some technicians to share their knowledge (which in some cases led us to start individual interviews with the concerned to extract their knowledge), the representation of uncertain knowledge, ambiguous concepts, and negative statements, as well as the processing of more complex and detailed information on some concepts. This sharing of knowledge via ontology allows each system to exploit all the knowledge of the other systems. As well, the reasoning methods, which can be applied to the ontology, provide a benefit to this knowledge while it can generate new knowledge that users cannot notice. Knowledge transfer is a powerful growth lever and an essential device for consolidating all the knowledge and intangible assets of a company. Today, knowledge is the strategic asset of the organization; hence the importance of encouraging teams and employees to develop a culture of sharing. Our work has been limited just to the extraction and collection of knowledge and the development of ontology. But, it remains a mandatory and essential step to open up new perspectives in a field very resistant to change. After this work, several challenges can be addressed. Indeed, in our future work, we will have the opportunity to exploit this knowledge base to set up tools that will be used for intelligent maintenance. For example, for the next work, we will try to take advantage of this step to develop a recommendation system for maintenance based on our ontology. Then give a surplus to maintenance technicians with the right information in the right format to the right people to do the right things at the right time. Moreover, the ontological model of our study has only integrated the pilot site, which is limited in terms of the type of rolling stock treated, the nature of the incidents, and the population of technicians. This component will be generalized to all maintenance facilities in our future work.

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