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## REVIEW

# A literature review on the applications of artificial intelligence to European rail transport safety

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## Abstract

In accordance with the current European railway regulations and particularly the two directives relating to the interoperability (Directive (EU) 2016/797) and safety (Directive (EU) 2016/798) of the railway system, this literature review proposes to classify artificial intelligence (AI) applications by distinguishing the structural elements (Infrastructure, Energy, Control-Command-Signalling and Rolling Stock) and the functional elements (Operation and Traffic Management, Maintenance and Telematics Applications) of the European railway system. Several “classic” AI techniques are implemented, including machine learning (supervised, semi-supervised, unsupervised), deep learning such as artificial neural networks (ANN), natural language processing (NLP), case-based reasoning (CBR), etc. However, the inadequacy of these approaches to capitalize, share and reuse the knowledge involved has oriented research towards the development of new approaches based on ontologies and knowledge graphs. This study shows that the stages of data acquisition, modeling, processing and interpretation pose a crucial problem in rail transport. In addition, with complex models described as “black boxes”, it is difficult to understand how the internal reasoning mechanisms of the AI system impact the solution and predictions. The new explainable AI (XAI) approach can possibly provide an element of response to this problem.

## 1 | INTRODUCTION

The ambitious goal of artificial intelligence (AI) is to equip computers with certain faculties of the human mind, namely learning, recognizing, reasoning, etc. Enthusiasm for AI and machine learning is now pervasive across all fields. The first research results concerned expert systems or knowledge-based systems (KBS), which have established themselves as decision support tools capable of reproducing certain intellectual tasks usually carried out by human experts. However, KBS rarely achieve the performance of human experts, and are often poorly adapted to the real needs of end users. This is due to the difficulty of extracting the necessary expertise from domain experts and representing this knowledge without distortion to build a cognitive model of the expert. Furthermore, capturing knowledge to store it in a knowledge base is a complex task that requires large material and human resources. Experts may have great difficulty explicitly describing the rea-

soning steps they use to make decisions, which may require a lengthy thought process to help explain the implicit and unconscious part of the process. Indeed, given the complexity of the expert's knowledge and the latter's difficulty in explaining his or her mental processes, the extracted knowledge can often be inaccurate, incomplete, or even incoherent. Various researches in AI has been carried out to address this problem of transfer of expertise. Knowledge acquisition methods, techniques and tools are now accessible to the knowledge engineer and providing a methodological framework for the development of KBS. In addition to knowledge-based systems (KBS), knowledge acquisition techniques (KA) and machine learning (ML) methods, AI implements several other methods and techniques often referred to as deep learning, such as neural networks (NN) also called deep learning, genetic algorithms (GA), pattern recognition often associated with image processing, fuzzy systems based on the theory of fuzzy sets proposed by Lotfi Zadeh in 1965, big data analytics (BDA),

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**TABLE 1** Reviewed journals and conferences related to the field of rail transportation safety.**Journals and conferences in alphabetical order**

Accident Analysis & Prevention	Journal of Loss, Prevention in the Process Industries
Advanced Engineering Informatics	Journal of Risk and Reliability
Applied Acoustics	Journal of Risk and Uncertainty in
Applied Sciences	JUCS-Journal of Universal Computer Science
Artificial Intelligence	Knowledge Acquisition, Media Info
Computer Standards & Interfaces	Lecture Notes in Computer Science, Springer
Computers in Industry	Nova Science Publishers
Data & Knowledge Engineering	Procedia CIRP
Engineering Applications of Artificial Intelligence	Procedia Computer Science
Engineering Systems, Part A: Civil Engineering	Procedia, Informatique
European Transport Research Review	Reliability Engineering & System Safety
Expert Systems with Applications	Safety Science
Future Internet, Information Fusion	Sage journals
IEEE Xplore / IEEE Transactions	Sensors
IGI Global	Transport Research Arena
International Journal of Environmental Research and Public Health	Transportation Engineering
International Journal of Electrical and Computer Engineering (IJECE)	Transportation Research Part C
IOS Press	Urban Rail Transit
Journal Information	Vehicle System Dynamics
Journal of Artificial Intelligence and Mechatronics	Wiley, Transactions in GIS
Journal of Computer Information Systems	

case-based reasoning (CBR), Internet of Things (IoT), cyber security, etc.

The study focused on around a hundred papers spread across around forty journals and conferences dedicated to rail transport. These journals are presented in Table 1 in alphabetical order.

The studied AI approaches applied to rail transport will be classified in accordance with European railway regulations and in particular the Directives related to system development (Directive 2012/34/EU [1]), railway interoperability (Directive 2016/797 [2]) and railway safety (Directive 2016/798 [3]) by distinguishing the structural elements (Infrastructure, Energy, Control-command and signalling and finally rolling stock) and the functional elements (operation and traffic management, maintenance and telematics applications) of the European railway system.

This document is organized into eleven sections. Section 2 provides an introduction to artificial intelligence (AI) and recalls the main machine learning (ML) methods and algorithms. Section 3 presents related work on AI applications in several transport sectors, in particular rail transport, intelligent transport, energy, water, transport and telecommunications infrastructure sectors. The contributions and limitations of this related work are specified in Section 4. In order to clarify and position AI work in the field of rail transport, it is appropriate to recall in Section 5 the European railway regulations. Directive (EU) 2016/797 on railway interoperability allowed us to

propose a decomposition of the rail transport system into structural elements and functional elements in order to identify the main railway subsystems, equipment and components. Directive (EU) 2016/798 on railway safety has led to the identification of the main concepts involved in safety and consequently to the identification of regulatory requirements in terms of railway safety. All of these identified concepts related to interoperability and railway safety are used in Section 6 devoted to a literature review on AI applications in rail transport. Within the framework of the “classical” AI approaches applied to rail transport, we distinguish:

- AI approaches related to structural elements such as rails, ballast, pantograph, axle, switch system, wheels, track geometry, rolling stock, etc.;
- AI approaches related to functional elements in particular telematics applications, Operation and traffic management, Maintenance, Safety in railway tunnels;
- AI approaches related to both structural and functional elements of the railway system;
- AI approaches related to railway safety: (1) Analysis of railway accidents based on investigation reports and (2) Analysis of railway accidents based on manufacturers’ files.

In addition to these “classic” AI approaches, this literature review is supplemented by other approaches based on ontology and knowledge graphs.

Section 7 provides a summary of these AI applications in railway transport and offers a classification in accordance with the European regulations previously mentioned. Section 8 positions this study in relation to railway regulations. Of the 65 articles examined 61% of the documents concern subsystems of a “structural” and “functional” nature, 26% are related to railway safety and finally 6% concern the harmonization of standards. The contributions and limitations of the AI approaches studied are presented in Section 9, which successively addresses 1) the challenges of AI data involved in rail transport and 2) explainable artificial intelligence (XAI) as a solution to improve “black box” models. Finally, after the conclusion (Section 10), the last Section 11 offers some perspectives for understanding the obstacles linked in particular to the problems of data involved in rail safety and explainability.

## 2 | INTRODUCTION TO ARTIFICIAL INTELLIGENCE (AI) AND MACHINE LEARNING (ML)

### 2.1 | Machine learning methods

Learning is reasoning: discovering analogies and similarities, generalizing or particularizing an experience, taking advantage of past failures and errors for subsequent reasoning. The objective is to explicitly represent a mass of knowledge or data, manage it, increase it and modify it with the aim of supporting decision-making. New skills are used to solve new problems, accomplish a new task or increase performance in accomplishing an existing task, explain a situation or predict behaviour.

When it comes to machine learning (ML), we distinguish between supervised learning, semi-supervised learning and unsupervised learning. In supervised learning, it involves learning to classify a new object (individual) among a set of predefined classes: we know the classes a priori. This involves learning a prediction function from annotated (or labelled) examples. On the contrary, in unsupervised learning, the number and definition of classes are not given a priori and it involves extracting classes or groups of individuals presenting common characteristics from unlabelled data. The semi-supervised learning approach lies between supervised learning which only uses known labelled data and unsupervised learning which only uses unlabelled data. This machine learning technique uses both a labelled and unlabelled dataset. In recent years and in the field of land transport, researchers and experts in the field have become increasingly interested in the application of AI techniques and in particular machine learning to solve certain decision support problems, such as transport equipment diagnosis, maintenance operations management, driver behaviour analysis, prediction of transport infrastructure deterioration, planning and forecasting of traffic demand, traffic light control, air traffic control, etc. These methods are also used to extract the presence of informative entities on recurring accidents and incidents with a view to understanding the causes of accidents and finding causal relationships from accident investigation reports. Thus, several

AI techniques are implemented: machine learning, deep learning such as artificial neural networks (ANN), big data, natural language processing (NLP) and CBR.

Data analysis, also called exploratory data analysis, aims to search for relationships between different data and to extract, by grouping, statistical information making it possible to describe in a succinct and clear manner the main information contained in this data. Statistical analysis methods therefore make it possible to collect and analyse data with a view to identifying patterns and trends and therefore making informed decisions. Data analysis relies on several *descriptive* and *inferential* techniques. These two statistical approaches, whose aim is to extrapolate results from data using statistical tests, rely primarily on the *median*, the *statistical mean* and the *standard deviation* to measure the magnitude of the data distribution relative to the average. The main mathematical tool used is *matrix algebra* based on a probabilistic model.

In this statistical context, we also speak of *regression* to study the link between variables, *hypothesis testing* to persuade whether a conclusion is correct for data collection, *cross-tab analysis*, *joint analysis*, etc. Principal component analysis (PCA) is a method that is part of the data analysis family. It is based on *regression* and *correlation* between several variables to describe the data by performing a *dimension reduction* of the training data (or training examples). The two main methods derived from PCA are correspondence factor analysis (CFA) and multiple correspondence factor analysis (AFCA or MCA) which is a generalization of factor analysis. Automatic classification and discriminant factor analysis (DFA) are two techniques that aim to identify similar groups within the training data set. The most recent analytical approach in data analysis is independent component analysis (ICA).

Non-negative matrix factorization (NMF) is a group of algorithms in multivariate (statistical) data analysis and linear algebra (or linear equations).

Some machine learning methods improve the prediction of elaborate models but at the expense of difficulty in interpretation and explanation in certain approaches, even the simplest ones, such as decision trees and linear regression models (least squares method, maximum likelihood model or even Bayesian inference) which generally seek to establish a linear relationship between a variable, called explained, and one or more variables, called explanatory (or predictive). Thus, in machine learning, the data is used to first train the algorithm on known (or labelled) data sets, then the learned model is used to predict unknown (unlabelled) values. SHAP (SHapley Additive exPlanations) is a technique for explaining and making understandable to humans the predictions of machine learning models [4]. It is based on “Shapley” values, which use game theory whose objective is to quantify the predictive power of a model based on these characteristics. It is therefore statistical learning as opposed to symbolic learning.

In the field of data mining and the retrieval of relevant information generally from accident investigation reports, there are several techniques from various fields, such as search for information (IR), natural language processing (NLP), information extraction (IE), machine learning and the BDA (big data

analytics) approach. BDA is beneficial considering the large amounts of data generated by the transportation system from sensors installed on tracks, on wagons or signalling equipment, monitoring and inspection of equipment, etc. A BDA can examine all the data collected in order to obtain useful information to explain, for example, the potential causes of operational degradation, failure of certain track components and possibly safety equipment. The main objective is to explore the raw text in order to extract relevant information for explanatory or decision-making purposes.

Natural language processing (NLP) or *linguistic engineering* is essentially based on stochastic methods such as information theory, and linear algebra, so-called probabilistic methods such as models Markov (or Markovian process) or so-called statistical methods such as machine learning and data mining. In the context of NLP, we speak of information extraction, text mining or search for significant information in a collection of given documents by using content indexing and recognition of entities designated by example the determination of proper nouns in a text. It is therefore appropriate to carry out similarity searches in texts, comparison of texts, and classification of texts into categories. We also talk about sentiment analysis and automatic document recommendation.

The main objective of NLP is to resolve certain difficulties related to the very long sentences involved in documents and which are sometimes ambiguous. To address this ambiguity, Markov models are frequently used. It is a Markov model if the state of the model at a time  $T$  depends exclusively on its state at time  $T - 1$ . A Markov model corresponds to finite-state probabilistic automata and the basic Markovian model corresponds to a simple (probabilistic) transition state diagram in the form of a graphical representation where the transition law expresses the evolution of the model, in the form of probability matrices where each describes the evolution of the model. Thus, we speak of an observable Markov model in the case where we can observe all the states in which the model is found at each moment. Otherwise, we speak of a hidden Markov model. Unlike a classic Markov chain where the states of an execution are known, a hidden Markov model (MMC) the states of an execution are unknown to the user. Hidden Markov models (or Markovian processes) are used specifically in the fields of NLP, pattern recognition, or generally in AI.

In the context of text mining of railway accidents in the United States, [5] used latent semantic analysis (LSA) and latent Dirichlet allocation (LDA). LSA (or latent semantic indexing) which is part of natural language processing relies on the use of a matrix describing the occurrence of certain terms (words) in documents. The LSA technique transforms the occurrence matrix into a “relationship” between terms and “concepts,” and a relationship between these concepts and the documents analysed. On the other hand, LDA also from NLP and which constitutes a probabilistic model based on data similarity measures makes it possible to explain sets of observations involved in documents.

Deep learning is essentially based on the artificial neural network (ANN) which is part of statistical AI applications allowing the creation of classifications of objects quickly. This notion of

deep learning is closely linked to deep neural network (DNN), deep belief network (DBN) and deep convolutional neural networks (DCNN). We speak of acyclic multilayer neural networks or multilayer perceptron's when the artificial neural network is organized in several layers. In addition to ANN, DNN, DBN and DCNN, there are several other types of networks: Convolutional neural network (CNN), long-term and short-term memory neural network (LSTM) and recurrent neural networks (RNN). For the detection of anomalies in the wheels of a train, [6] used four unsupervised learning techniques including multilayer perceptron autoencoder (MLP-AE). In the literature, we also speak of convolutional neural network autoencoder (CNN-AE). An autoencoder, whose objective is to reduce the size of the data set, is a type of somewhat special artificial neural network architecture used for unsupervised learning of discriminative characteristics. It is designed to compress (encode) input data to its essential characteristics, then restore (decode) the original input from this compressed reproduction.

In the context of rail transportation systems, a digital twin is a complex computerized model that considers the dynamics of trains, vehicles and tracks, as well as the interaction of wheel-rail contacts. A standard (non-augmented) train digital twin can use measurements from multiple sensors located on board the train or on the ground (infrastructure) as feedback linked for example to an automated train control (ATO) system whose objective is the management of train control commands. In contrast, an “augmented” digital twin uses the same feedback as input to a surrogate model which, in turn, uses the sensor data to estimate the state of the system dynamics, thus enabling feedback more complex at the ATO which operates the train control commands [7].

Case-based reasoning (CBR) is a well-established area of research based on AI techniques, particularly machine learning. It is attracting more and more attention from researchers and experts in the rail transport sector. The studies include the diagnosis of locomotive breakdowns, the prevention of railway operating incidents, the analysis of safety risks linked to metro operation, automatic train driving and finally the diagnosis of railway manoeuvring system faults. This mode of reasoning, which is based on the notion of similarity, focuses above all on problem solving based on experience. It is a cognitive process of human reasoning that relies largely on how individuals acquire a new skill based on their past habits and experiences.

Several other methods, techniques and theories are used in AI applications dedicated to rail transport such as the Petri Net, expert systems, fuzzy logic, short-time Fourier transform (STFT) or again learning by gradient back propagation (or gradient back propagation technique) which is based on the gradient algorithm also called the gradient descent algorithm or the differentiable optimization algorithm. Some work refers to computational intelligence (CI) which is traditionally based on the following main pillars: artificial neural networks, fuzzy systems, evolutionary computing (or evolutionary computing) and probabilistic methods. The finite element method and the theory of complex networks are also part of the AI applications studied.



## 2.2 | Machine learning algorithms

There are several machine learning approaches and algorithms that rely largely on regression, discrimination (or classification), and clustering techniques. The *grouping* that we call *classification* in data analysis (or supervised learning in AI) consists, from a mass of data, of discovering common features between this data so that we can group them into simpler subgroups and having meaning. The vast majority of grouping procedures are digital in nature. *Discrimination* aims at learning classification procedures. From a set of examples of concepts, the aim is to find a technique that allows each concept to be recognized. The vast majority of existing methods are based on numerical evaluations. Statistical *regression* (simple linear, multiple, logistic, or logarithmic) is a supervised learning approach that uses an algorithm not only to understand the relationship between dependent and independent variables, but also to predict numerical values. Finally, the problem of *generalization* consists, from concrete examples of a situation, of finding a fairly general formula to describe this situation and explaining the descriptive capacity of this formula.

*Regression* covers several methods of statistical analysis, as opposed to classification. In machine learning, statistical regression can be a linear or multilinear regression whose objective is the prediction of a “quantitative” variable, while “classification” aims to predict a “qualitative” variable. A linear classifier is a particular type of statistical classifier whose objective is to encrypt a decision by linear combination of samples which have similar properties, measured on observations. *Support vector regression (SVR)* is a generalization of linear classifiers and is based on the implementation of statistical classification algorithms used for regression analysis.

The SVR, whose performance is sometimes identical to a neural network, is a supervised learning technique allowing the resolution of problems linked to *discrimination* and *regression*. *Discrimination* is a statistical approach such as discriminant factor analysis (DFA). Statistical *regression* covers several methods of statistical analysis (linear or multilinear) with a view to predicting a *quantitative* variable as opposed to classification which aims to predict a *qualitative* variable.

The *nearest neighbour's algorithm (KNN)* aims to predict the membership of a new piece of data (or observation) to a family or class of objects by calculating the distance of the new observation from the set of training examples. The objective is to find the most representative membership class and therefore the class closest to the new observation (entry)  $X$  among the  $K$  entries. The  $k$ -NN algorithm is an approach for classification and regression and is the simplest supervised machine learning algorithm. In classification, the result is a membership class according to the majority result of class statistics: If  $k = 1$ , then the object is assigned to the class of its close neighbour. In regression, the result is the average value of the nearest  $k$  values.

Belonging to the family of linear classifiers, *naive Bayesian classification* is a type of simple probabilistic Bayesian classification based on Bayes' theorem which depends strongly (naively) on hypotheses and is based on maximum likelihood which is

a statistical approach whose goal is to find the most plausible parameters of a probability model to explain observed data. The naive Bayesian classifier is part of supervised learning approaches and therefore requires that the classes of the training dataset are known. However, studies have shown that random forests, particularly *decision trees*, provide better results.

Learning *decision trees* (or random forests or forests of decision trees) is one of the machine learning techniques which constitutes a decision support tool whose objective is to represent different possible decisions in the form of a graphic tree. From the work of Quinlan in [8], a decision tree is a set of choices in the graphic form of a tree and the possible decisions are located at the “leaves” of the tree. From the decision tree, we can generate classification rules. When we have a large dataset containing several variables, we seek not only to discover the most important variables, but also to reduce this dataset in order to represent it in a simple way. This is the main objective of *principal component analysis (PCA)* which constitutes one of the most frequently used methods of multivariate data analysis. It is often considered a data mining method because it makes it easy to extract information from large data sets.

*K-means* is one of the unsupervised learning methods whose objective is the grouping (or clustering) of several observations into  $K$  clusters (groups) by comparing the degree of similarity between the different observations based often over the Euclidean distance. Thus, unlike supervised learning whose goal is to learn a correlation relationship between a set of data in order to predict the class of membership of a new observation, in unsupervised learning based on  $K$ -means, the objective is rather to discover patterns in the learning database in order to group objects that look similar.

## 3 | RELATED WORKS ON THE APPLICATION OF AI IN RAILWAY TRANSPORTATION

In the field of transportation, several approaches to classification of AI and machine learning techniques have been proposed in recent years in [9, 10].

In the field of *intelligent* transportation, [9, 11] have proposed several applications of AI. In *public transport*, several applications of AI have been studied in [12]. An interesting study was proposed as part of the work of [13] on the applications of AI techniques, methods and algorithms in the energy, water, transport and telecommunications *infrastructure sectors*. Ref. [14] studied the applications of AI in *different modes of transport*: land (road, rail), maritime and air. The challenges, arguments and interests of “Big Data” for risk management in *rail transport* have been presented in [15–17].

After giving an overview of “Big Data” technologies in the *rail transport* sector, [18] presented an interesting survey from 2003 to 2017 on the potential applications of big data analysis in railway systems rail transport. The authors proposed a classification of AI methods, models and algorithms involved in the analysis of railway data. The authors also

proposed a classification of Big Data applications in the field of rail transport by distinguishing three levels of analysis:

- Analysis by zone which brings together upkeep/maintenance tasks, tasks linked to operation which concerns route choice, train positioning, demand forecasting, disruption management, etc. and tasks relating to safety, in particular the analysis of risk, severity and frequency;
- Analysis according to the type of maintenance (corrective, preventive and conditional);
- Analysis based on the equipment of the railway system which distinguishes the vehicle, the track and the signalling equipment.

According to [19], the areas of application of Industry 4.0 technologies in *rail transport* relate to the following three branches:

- Surveillance which concerns the detection of irregularities in the rails, inspection of railway axles, monitoring of freight trains, etc.;
- Decision and planning to predict train arrival times, perform maintenance operations, minimize traction energy, minimize train delays, etc.;
- Communication and safety to monitor overcrowding in station areas, use of AI camera and graphics processing units (GPUs), travel connectivity, etc.

Applications in the field of *rail transport* relate to monitoring, decision-making and planning techniques as well as communication and safety [19]:

- The monitoring area covers both the monitoring of railway infrastructure (detection of irregularities in rails, inspection of railway axles) and assistance systems for the driver of freight trains;
- The area of communication and safety covers railway safety to monitor overcrowding in station areas, safety systems which include AI cameras and graphics processing units (GPUs) ultimately travel connectivity;
- The field relating to decision and planning focuses on optimizing rail transport by establishing predictions on the arrival times of freight trains, providing information on transport using big analysis Data to improve, for example, the maintenance process, to optimize and minimize train traction energy as well as train delays.

In the field of *railway transport safety*, [10] proposed a detailed study of the causes of railway accidents which distinguishes the causes linked to accidents at level crossings, to the safety of railway construction, to the asset management, human factors and technical malfunctions. As part of this study, the authors examined in particular the roles of humans and organizations in the train accident process, the train collision accident, the quantification of accidents, the prediction of the structural integrity of a railway bridge and the prediction of geometric defects of railway tracks. Finally, the authors [20] proposed a conceptual frame-

work called “HazardMap” which is based on the open source natural language processing thematic model “BERTopic” in order to analyze textual data from the “Rail Accident Investigation Branch” (RAIB), the Australian Transport Safety Bureau (ATSB).

Finally, [21–23] have proposed consistent studies on the applications of AI in the field of rail transport. Ref. [21] presented a critical review of recent textual research and their applications in railways which notably concern the analysis of accidents and incidents, sentiment analysis in particular passenger complaints and speech synthesis, detection of technical specifications, fault diagnosis, servicing/maintenance and inspection, accident risk assessment, extraction of safety information, identification of accident causes and finally the identification of maintenance events. An interesting taxonomy of artificial intelligence methods and algorithms as well as their applications in rail transport has been proposed in [22]. The applications identified by the authors relate to autonomous train driving and control, maintenance and inspection in particular fault diagnosis, infrastructure condition monitoring, fault detection and prediction, mobility of passengers which includes the prevention and prediction of passenger flows and passenger satisfaction, traffic planning and management, finally safety and security of transport in particular the analysis of incidents, station security, detection of defects, rail disruptions and research into the causes of accidents. Finally, [23] also proposed a literature review on the applications of AI in railway transport systems and the applications studied concern autonomous driving and control, revenue management, inspection, passenger mobility, traffic planning and management, transport policy and safety and security.

#### 4 | CONTRIBUTIONS AND LIMITATIONS OF RELATED WORK AND OBJECTIVE OF THE STUDY

Despite the certain interest of work on the applications of AI to the field of rail transport, several important methods for rail safety such as ontologies, knowledge graphs, case-based reasoning (CBR) have not been considered by previous work. Furthermore, there are ambiguities and several confusions in terms and concepts related to rail transportation safety. This work proposes to complete previous work by including other work on ontologies and knowledge graphs essential to better explain and integrate knowledge in the field of rail safety, and thus clarify certain essential concepts in rail safety management by using the regulations in force, in particular the three European directives relating to the development, interoperability and safety of the European railway system:

- Development: Directive 2012/34/EU of the European Parliament and of the Council of 21 November 2012 establishing a single European railway area (recast);
- Interoperability: Directive (EU) 2016/797 [2] of the European Parliament and of the Council of 11 May 2016 relating

to the interoperability of the rail system within the European Union (recast), (Consolidated version of 28 May 2020);

- Safety: Directive (EU) 2016/798 of the European Parliament and of the Council of 11 May 2016 on railway safety

These directives will be used to specify all the structural and functional subsystems, equipment and components of a European railway system. The main objective is to clarify and position the contribution of AI techniques in relation to European rail transport legislation and regulations and therefore promote the interest in new AI approaches by the European Commission, national safety authorities and the railway operators in particular the infrastructure manager (IM), the railway undertakings (RU), the entities responsible for the maintenance (ECE) of the railway system.

## 5 | EUROPEAN RAILWAY REGULATIONS

### 5.1 | Decomposition of the rail transport system in accordance with European regulations

According to Directive (EU) 2016/797 [2] of the European Parliament and of the Council of 11 May 2016 on the interoperability of the railway system within the European Union, railway systems, equipment and components present significant differences due to the fact that they integrate particular techniques specific to the national railway industry and therefore include particular dimensions and devices, as well as special characteristics. This situation may prevent trains from traveling without obstacles throughout the European Union. It is therefore essential to define essential requirements and new technical specifications relating to railway interoperability, called TSI (technical specifications for interoperability). A TSI specifies all the conditions that an interoperability constituent must respect as well as the procedure to follow for conformity assessment. Therefore, the TSIs provide the necessary framework to decide whether existing railway subsystems require a new authorization for placing in service or placing on the market. Directive (EU) 2016/797 [2] establishes the conditions that must be met to achieve interoperability within the Union rail system in compliance with Directive (EU) 2016/798 on safety. The objective is to define an optimal level of technical harmonization, improve and develop rail transport services within the European Union. In this context, and taking into account the complexity of the Union's rail system and in order to promote interoperability and safety, it was necessary, for practical reasons, to break it down into several subsystems that are simpler to understand: "infrastructure", "rolling stock", "energy", "control-command and signalling on the ground", "control-command and signalling on board", "operation and traffic management", "maintenance", "telematics applications for the service of passengers and the service of freight." This paragraph provides a summary of all the elements and constituents of the Union rail system in accordance with the following two directives:

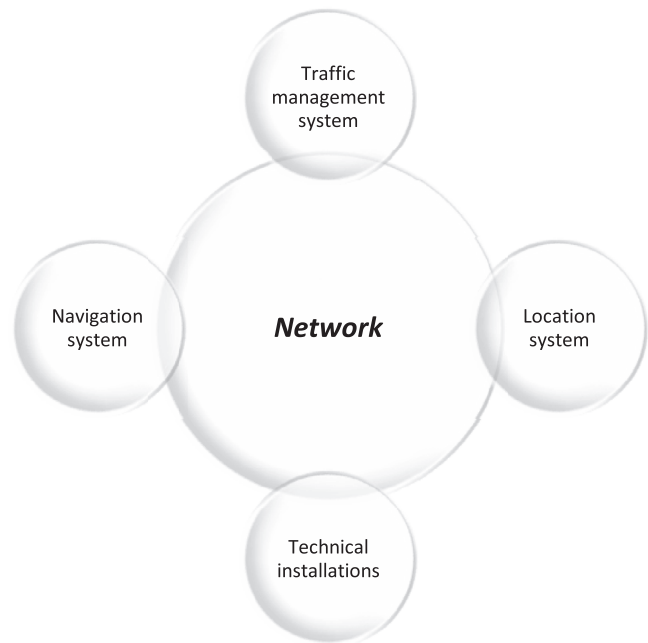


FIGURE 1 Main subsystems involved in the railway network.

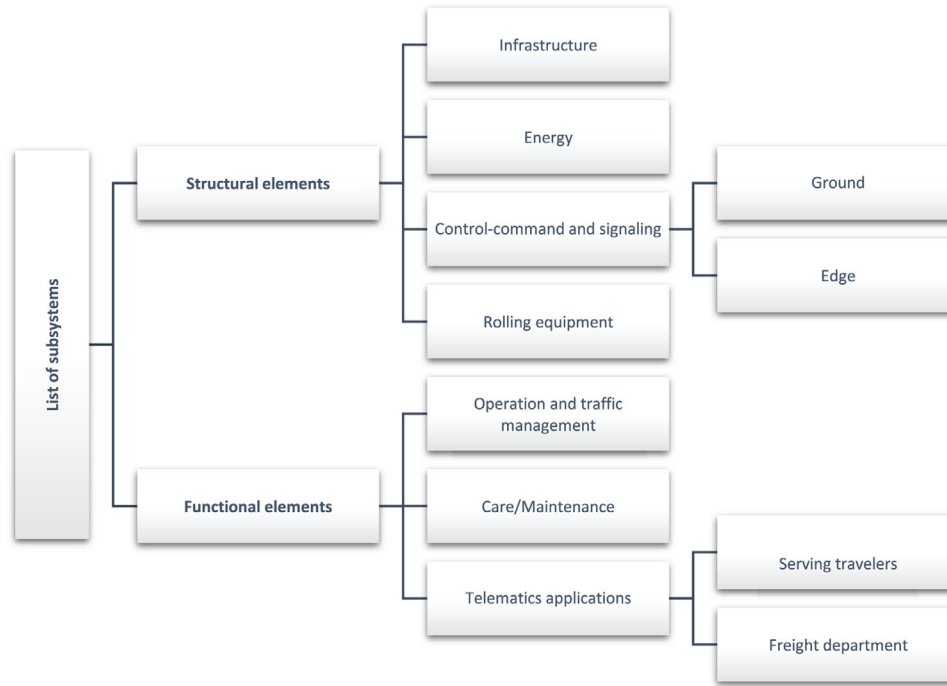
- Directive 2012/34/EU of the European Parliament and of the Council of 21 November 2012 [24] establishing a single European railway area (recast);
- Directive (EU) 2016/797 [2] of the European Parliament and of the Council of 11 May 2016 on the interoperability of the railway system within the European Union (recast).

Annex I of Directive 2012/34/EU provides a list of elements of the railway infrastructure: land, body and platform of the track, structures, superstructure, carriageways of passenger and goods yards, safety, signalling and telecommunications installations, lighting installations, electrical current transformation and transmission installations for the traction of trains and buildings assigned to the infrastructure service. For example, the superstructure includes the following elements: rails, grooved rails and counter rails; sleepers and sills, small assembly equipment, ballast, including gravel and sand, track switches, turntables and transporter trolleys. Annex I to Directive (EU) 2016/797 [2] breaks down the elements of the Union rail system into fixed and mobile elements including:

- The network, made up of lines, stations, terminals and any type of fixed equipment necessary to ensure its operation,
- Vehicles circulating on this network. Each vehicle is made up of a "rolling stock" subsystem, other subsystems, particularly the "control-command and on-board signaling" subsystem.

This network includes traffic management, location and navigation systems, technical data processing and telecommunications facilities provided for long-distance passenger transport and freight transport on this network in order to guarantee safe operation and harmonious network and efficient traffic management (Figure 1).





**FIGURE 2** Structural and functional decomposition of European railway subsystems.

In accordance with Annex I to Directive (EU) 2016/797 [2], Union vehicles include all vehicles capable of circulating on all or part of the Union network:

- Locomotives and rolling stock intended for the transport of passengers, including traction units with thermal or electric motors, multiple units with thermal or electric motors, as well as cars,
- Freight wagons, including low-loaders designed for the entire network and vehicles designed for the transport of trucks,
- Special vehicles, such as track machinery.

Annex II of the same Directive (EU) 2016/797 [2] also provides a functional and structural description of the elements of the Union rail subsystems summarized in Figure 2.

The main subsystems, equipment and interoperability constituents from the two European directives (Directive 2012/34/EU and Directive (EU) 2016/797 [2]) are summarized in Figure 3.

## 5.2 | Regulatory requirements for railway safety

Directive (EU) 2016/798 of the European Parliament and of the Council of 11 May 2016 on railway safety, which is one of the legislative acts covering the technical aspect of the 4th railway package, established several measures intended to develop and improve the rail safety in the EU. We are only interested here in the safety requirements imposed by this directive both on the European rail system and on all rail stakeholders and

in particular: Article 5: Common Safety Indicators (CSI); Article 6: Common Safety Methods (CSM); Article 7: Common Safety Objectives (CSO); Article 9: Safety Management Systems (SMS); Article 10: Safety Certificate; Article 12: Safety Approval; Article 14: Vehicle Maintenance and Article 17: Safety Monitoring.

All of these requirements are summarized in Figure 4. Rail safety management involves two main phases: Safety construction and safety management. To build safety, it is appropriate to first define a safety objective (or safety target levels) which is often quantitative and expresses risk acceptance criteria with regard to the individual risks to which passengers and passengers are exposed personal and with regard to collective risks (risks for society). To achieve these safety objectives, it is necessary to define essential safety requirements (qualitative or quantitative) which are imposed on the system during its operation and maintenance. The essential requirements from Annex III of Directive (EU) 2016/797 [2] concern not only safety, but also reliability, availability, health, etc. There are two types of essential requirements: “general” requirements and “particular” requirements imposed on each subsystem. The essential requirements of “general scope” linked to “safety” relate to the development, maintenance and monitoring of critical (or essential) components for safety and mainly the equipment and functions involved in the movement of trains including the objective is to guarantee safety. The “particular” essential requirements linked to “safety” concerns all subsystems: infrastructure, rolling stock (RS), control-command and signalling, etc. For example, the “particular” essential requirements linked to the “safety” of the RS subsystem relate to: (1) the structures of the RS and the connections between the vehicles which must

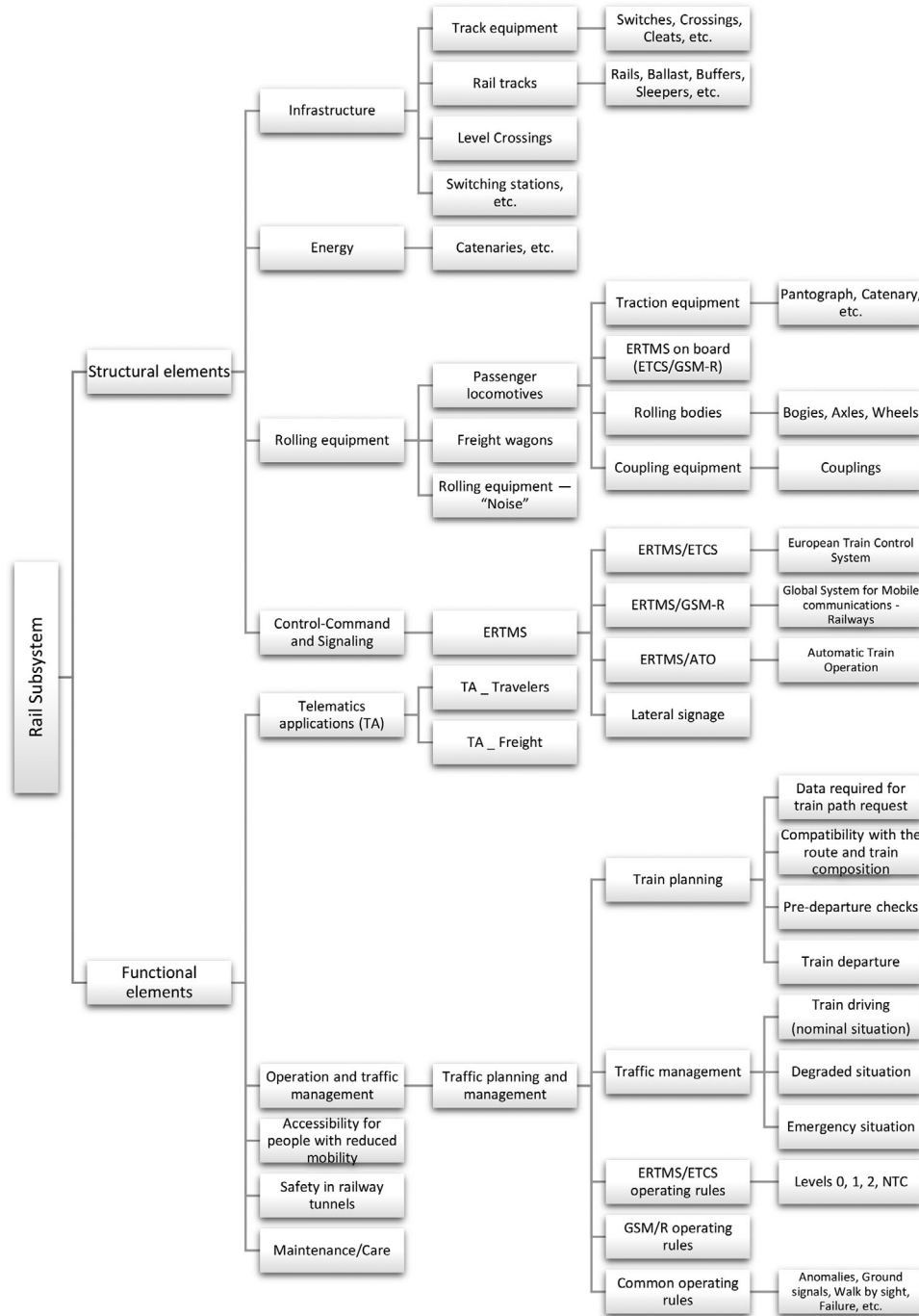


FIGURE 3 Main subsystems, equipment and constituents of railway interoperability.

be designed in such a way as to protect passengers in particular in the event of a collision or accident or derailment of the train, and (2) on the safety of passengers when boarding and disembarking from trains, in particular access doors must be equipped with a closing and opening system which guarantees the safety of passengers.

To build safety, each railway operator (infrastructure manager (IM), railway company (RC) and entity in charge of maintenance (ECM)) must develop its safety management system (SMS). An

SMS establishes by the RC for obtaining a safety certificate, an SMS developed by the IM for obtaining a safety approval and a maintenance system implemented by the ECT Directive (EU) 2016/798 imposed several MSCs: (1) MSC for the assessment of the achievement of CSO, (2) CSM for the assessment of compliance with safety requirements for the issuance of RC safety certificates and IM safety approvals, (3) CSM for the evaluation and assessment of risks in accordance with Implementing Regulation (EU) No 402/2013 [25] and in particular in the event



FIGURE 4 Main safety requirements according to the railway safety directive.

of a significant change, (4) CSM for control by the RUs after obtaining a single safety certificate and control by the IMs after obtaining a safety approval and finally the control by the ECMs after obtaining a vehicle maintenance certificate, (5) CSM for the surveillance carried out by the national safety authorities (NSA).

Thus, after having built safety, it is appropriate to manage and manage safety (Figure 4) by considering in particular the management of changes (modifications), the control of safety by the railway operators, the monitoring of safety by the NSA and finally the management of feedback which requires two main

stages: (1) the collection of *significant* accidents in accordance with common safety indicators (CSI) and (2) investigations into *critical* accidents by independent organizations with a view to analysing the causes railway accidents and to propose measures to improve safety. ISCs make it possible to assess the conformity of systems with respect to common safety objectives (CSO) and thus facilitate the monitoring of the evolution of railway safety performance. Member States collect information on SAIs using annual safety reports prepared by NSAs. The European Commission, through the European Union Agency for Railways, examines rail transport statistics with a view to assessing national reference values (NRVs) which are reference measures indicating, for a Member State, the maximum acceptable level for a railway risk category. The VNRs are defined by the European Commission (2nd series of CSO: Decision No2012/226/EU [24] and Implementing Decision (EU) No 2013/753 [26]) in order to quantify the expected performance in terms of railway safety. The achievement of these objectives is evaluated annually for year A-2 for different categories of risks linked to passengers, employees, users of level crossings (LC), unauthorized persons (intruders), “other” persons and to the whole of society.

The main subsystems, equipment and constituents of railway interoperability (Figure 3) as well as the main railway safety requirements (Figure 4) are summarized in Table 2.

## 6 | LITERATURE REVIEW ON AI APPLICATIONS IN RAIL TRANSPORT

### 6.1 | Applications of “classic” AI in rail transport

After quickly presenting the main safety requirements imposed by European legislative acts and in particular Directive (EU) 2016/798 relating to railway safety, after having presented the main subsystems, equipment and functions imposed by directive (EU) 2016/797 [2] relating to the interoperability of the railway system, the objective of the following bibliographical study on the applications of AI methods in the field of railway safety seeks to position these methods in relation to the regulations in force: Directive (EU) 2016/797 [2] and Directive (EU) 2016/798.

#### 6.1.1 | AI approaches related to structural elements of the railway system

Railway tracks (Rails): In the context of structural elements and precisely railway tracks [27], established a solution for the automatic detection of rail surface defects based on deep convolutional neural networks (DCNN). Image data for rail surface defect detection is obtained from automated video recordings (camera with high frame rate). 22,408 objects (collected image data) were manually labelled according to six classes: normal, weld, mild squat, moderate squat, severe squat and joint. Ultimately the set of training examples contains 985 welds, 938

mild squats and smaller insignificant defects, 562 moderate and severe squats and 755 rail joints. The DCNN are used to recognize the characteristics of the collected images and therefore automatically detect rail defects. The study showed that 61.95% of defects related to weld defects are correctly classified, while 30.97% of actual welds are classified in the normal class.

Also based on convolutional neural networks (CNN), [28] proposed an approach for inspecting rail surface defects using deep learning and 3D laser cameras. Several types of rail surface cracks are considered in this study such as cracks caused by manufacturing defects, welding defects, hairline cracks which appear on the surface of the rails, defects linked to corrugation in particular defects in railway tie connections, excessive or unbalanced loads and the presence of rail depressions.

Railway tracks (Ballast): Still in the context of railway tracks but this time concerning Ballast (crushed stones that are packed under the sleepers of a railway track), [29] have developed an expert decision support system for the maintenance of railway ballast which is based on the joint use of expert systems, Petri Networks and deep learning. Based on the track maintenance history (track data), the objective of this study is to identify the appropriate ballast maintenance action to remedy the problem of jamming and stone blowing, renewal or absence of intervention. This condition-based maintenance approach was applied to a railway with ten sections, 2830 states and four actions per state.

Traction equipment (Pantograph): In order to improve the operation and maintenance of the Pantograph which is part of the traction equipment of rolling stock, [30] applied machine learning to data from the pantograph of an operator’s rolling stock South African railway. This learning approach based on automatic classification was used to identify, from a pantograph dataset, potential hazardous events related to train traction equipment and therefore, understand whether “pantograph bounce” occurs due to faulty sensors, faulty pantographs or faulty infrastructure.

Running gear (Axle): Generally, two types of axle are considered in rail transport: the classic axle (also called bare axle) which is composed of two railway wheels and an “axle” and the bent axle which is also composed of two wheels but with two independent axes connected by another element, often the frame of a “bogie” (carriage located under a vehicle on which the axles and therefore the wheels are fixed) or a locomotive “chassis”. A railway axle, which rides on the rails allowing the movement and guidance of the vehicle, plays an important role in the safety of the train by preventing derailment. Therefore, predicting “wheelset” degradation is essential for effective and sustainable maintenance planning. Due to contact forces and friction with the rails, wheels can become damaged and worn, changing their profile shape. Thus, the condition of the wheels generally determines the lifespan of the wheelset and monitoring the level of wheel degradation therefore requires permanent monitoring of the evolution of the geometric variables involved in the wheel profile.

In this context, [31] proposed a data-based decision support system to improve the condition-based maintenance of a railway axle. Maintenance and inspection data carried out on the



**TABLE 2** Summary of European rail transport subsystems and safety requirements imposed by the directives.

“Structural” subsystem		“Functional” subsystem		Railway safety
Subsystem	Equipment	Interoperability constituents (examples)	Subsystem	Functional elements
– Infrastructure, Energy, Rolling stock (Locomotive), Rolling stock (Wagons), Rolling stock (Noise).	Ground equipment, Aerial equipment, Railway Track Equipment, Railway tracks, Level Crossings (LC), Signalling post, Mating equipment, Braking equipment, Running gear, Braking equipment, Traction equipment, ERTMS on board (ETCS/GSM-R), ERTMS ground (ETCS/GSM-R), ETCS: European Train Control System, GSM-R: Global System for Mobile communications—Railways, ATC: Automatic Train Operation	Substations, Power lines, Catenaries: Overhead contact line (OCL), Connections (railway switches), Crossings (crossing tracks), “Derailleurs” or “stop” cleats, Rails, Ballast, Knocker (stopper), Railway sleepers, Couplings, Pantograph, Catenary, Bogies, Axles, Wheels, Etc.	– Control-Command and Signaling, – Telematics applications (TA), – Operation and traffic management, – Accessibility for disabled people and people with reduced mobility, – Safety in railway tunnels, – Care/Maintenance.	– Safety requirements, – National reference value (NRV), – Common security objectives (CSO), – Common safety indicators (CSI), – Safety certificate, – Safety approval, – Safety management system (SMS), – Common security methods (CSM), – CSM_Risk assessment (CSM-R), – CSM_Evaluate the achievement of common safety objectives (CSO), – CSM_SMS control, – CSM_Monitoring, – Safety integration, – Safety-critical (or essential) tasks, – Change Management (Modifications), – Accident and incident investigation.
				– TRAIN PLANNING: Data for train path request, Train composition, Compatibility with the route and train composition, Pre-departure checks (Loading, Braking, Doors), Train departure.
				– TRAFFIC MANAGEMENT, – OPERATION IN NOMINAL SITUATION (Train identification, Line, Timetable, Dangerous goods, Train driving, Traffic conditions, Data recording, Emergency braking, Crossing, Train speed, Train monitoring, Ground signalling anomalies, Equipment failure Edge or Ground, Emergency call, Communication, Authorization to pass a stop signal, etc.),
				– OPERATING IN DEGRADED SITUATION (On-sight operation, etc.),
				– EMERGENCY OPERATION (Accidents, Fires, Emergency situation requirements, Evacuation requirements, Material requirements, Fire detection and prevention, reliability of electrical installations, etc.)
				– OPERATING RULES: ERTMS/ETCS operating rules (Levels 0, 1, 2, NTC), GSM/R operating rules, Common operating rules.

running gear have been collected and represent the Axle degradation records. Several characteristics of the degradation data were analysed, such as wheelset type, material, position, vehicle, distance travelled, wheel profile parameters and weather conditions. Statistical analysis methods were used to process this degradation data. According to the authors, “*the results show that kilometres since last turn/renewal (race distance) is the variable with the most influence on axle wear trajectories among all variables analysed and is statistically significant in each model*”.

**Connections (Switch system):** Track devices installed in a railway infrastructure mainly concern connections (or switches), crossings (or crossing of tracks), “derailleur” or “stop” cleats, etc. Ref. [32] proposed an approach for diagnosing faults in the railway switching system based on case-based reasoning (CBR) whose objective is to solve a new case (problem without solution) by recovering similar cases stored in a case database and adapting them to the new case to be solved. The main steps in a CBR process are: (a) searching and retrieving the most similar cases, (b) reusing existing source case knowledge (historical case base) to solve the new problem, (c) revising the proposed solution if necessary, and (d) retaining the new solution for solving a future problem. The implementation of learning based on CBR requires similarity measures to search for the case most similar to the problem to be treated. The similarity measure based on the Euclidean distance metric is one of the most popular measures used to measure the similarity of digital data.

**Rolling elements (Wheels):** Railway wheels are part of the rolling elements of rolling stock (passenger locomotive or freight wagon). Two works studied the diagnosis and detection of faults and anomalies in railway wheels. Ref. [33] used a fuzzy logic method for the diagnosis of railway wheel defects. Ref. [6] used algorithms based on the short-term Fourier transform (STFT) and unsupervised learning for the detection of anomalies in the wheels of a train. STFT was used to extract the “time-frequency” characteristics of the collected vibration signal. Long-term and short-term memory neural network (LSTM) is applied to learn dynamic changes in track geometry data. Four unsupervised learning algorithms were used and compared to derive five health indices for monitoring the condition of train wheels: Non-negative matrix factorization (NMF), one-class support vector machine (OC-SVM), multilayer perceptron autoencoder (MLP-AE) and convolutional neural network autoencoder (CNN-AE). The training data considered in this work is historical data provided by a railway consulting company and was collected using a fibre Bragg grating (FBG) sensor system installed on a straight track of a commuter rail line in Southeast Asia. Finally, the comparison of the four learning algorithms implemented indicates, according to the authors, that the two approaches NMF and MLP-AE outperformed the other approaches: OC-SVM and CNN-AE. Indeed, the MLP-AE approach offers better performance in detecting anomalies in the wheels of a train while the NMF approach is less expensive in terms of calculation.

**Railway tracks and track geometry:** In the context of “Structural equipment/Infrastructure/Railways/Track geometry” and based on track inspection data from American Class I freight railway lines, [34] have proposed a railway track geometry

change prediction approach based on a hybrid machine learning model combining a convolutional neural network (CNN) and a long-term and short-term memory (LSTM) neural network. The CNN was used to capture the spatial features with the historical geometric data of different track segments as inputs. LSTM was applied to learn dynamic changes in track geometry data. To demonstrate the feasibility of the proposed approach, the case study was carried out based on inspection data from approximately 80 miles of American Class I railway tracks. Several types of data were used: historical data track geometry, infrastructure data and operational data such as traffic, speed, slope and curvature.

Still regarding railway tracks, [35] developed a deep learning approach for the inspection of railway tracks based on neural networks and [36] proposed a method of machine learning for predicting breakdowns on railway tracks for two high-speed lines in Spain. In [36], it is a learning by back propagation which brings together: (1) the multilayer perceptron trained with the BFGS algorithm, (2) the recurrent neural networks of ELMAN and (3) the support vector regression (SVR). In this context of multiple learning, we often speak of computational intelligence (CI) which is traditionally based on the following main pillars: artificial neural networks, fuzzy systems, evolutionary computing (or evolutionary computing) and probabilistic methods. In the context of this application for predicting breakdowns on high-speed lines in Spain, the authors highlight that ELMAN’s recurrent neural networks and support vector regression (SVR) outperform other learning methods and in particular statistical models. Furthermore, the two high-speed lines have slightly different error rates, which the authors say requires further detailed study of the data characteristics of the two lines in order to minimize the error. Data preprocessing techniques also need to be further explored to improve the results. Finally, the authors consider that expert knowledge in the railway field may be essential to complete the data considered in this study.

**Rolling stock (locomotive or vehicle):** Based on the artificial neural network (ANN) and particularly the deep belief network (DBN) and from historical data on the breakdowns of the Wuhan-Guangzhou TGV (China) from 2011 to 2013, [37] developed an approach to fault diagnosis of on-board equipment in high-speed rail vehicles. The equipment included in this study is: train speed control unit (ATPCU); compact antenna unit (CAU); beacon transmission module (BTM); radio transmission module (RTM); speed-position unit (SPU), etc.

**Rolling stock (Wagons):** If the previous diagnostic approaches concern locomotives (or vehicles) intended for passenger transport, [7, 38] have proposed approaches this time concerning wagons which are intended for the goods (or freight). Ref. [7] proposed a “digital twin” based on machine learning to predict the risk of derailment of a freight wagon. As for [38], they developed a predictive maintenance framework based on machine learning to assign a health score to railcar fleets in the United States.

In the context of rail systems, a digital twin is a complex computerized model that considers the dynamics of trains, vehicles and tracks, as well as the interaction of wheel-rail contacts. A standard (non-augmented) train digital twin can

use measurements from multiple sensors located on board the train or on the ground (infrastructure) as feedback linked for example to an automated train control (ATO) system whose objective is the management of train control commands. In contrast, an “augmented” digital twin uses the same feedback as input to a surrogate model which, in turn, uses the sensor data to estimate the state of the system dynamics, thus enabling feedback more complex at the ATO which operates the train control commands. As part of the work of [7], this is an augmented digital twin for railway applications (ADTR), envisaged to work with an ATO. To predict the derailment of a wagon, several input data were considered such as the composition of the train, the speed of the vehicle, the curve radius and the lateral coupling forces in real time. The derailment index was calculated from the results of the multi-body wagon simulation (MBS) using wheel unloading (WU) and the ratio between vertical and lateral forces for each wheel set ( $L/V$ ).

Ref. [38] proposed a machine learning-based predictive maintenance framework to assign a health score to railcar fleets in the United States for decision making. Three AI approaches were used: (1) classification learning (Random Forest and decision trees), (2) principal component analysis (PCA) and (3) expert system. The random forest model is used to predict whether or not a railcar component will need to be replaced.

PCA (principal component analysis) algorithm is applied to improve the accuracy of fault diagnosis and finally the expert system to improve railcar maintenance planning decisions. Historical repair and inspection data was collected for four components of a specific railcar type from 1986 to 2020. The fleet selected for the study contains approximately 11,000 active railcars. The data from this maintenance support system considers the age of the wagons, the geographic loading history, the kilometres travelled, the replacement history of the components and the condition of the components (new or refurbished). Based on the identification of critical components of the system and their failure probabilities, the supervised learning model provides a measure of the state of health (rate) associated with each wagon.

Railway crossing: Based on feedback, [20] proposed a conceptual framework called “Hazard Map” to understand the dangers linked to railway accidents at level crossings. For this purpose, the authors used the open source natural language processing model “BERTopic” for the automated analysis of textual data from the Rail Accident Investigation Branch (RAIB), the Australian Transport Safety Bureau (ATSB), the National Transportation Safety Board (NTSB Rail Accident Reports) and the Transportation Safety Board of Canada (TSB).

### 6.1.2 | AI approaches related to functional elements of the rail system

#### *Telematics applications (TA)*

Two studies related to the functional elements of the railway system and more precisely telematics applications (AT) will be presented later in the context of ontology-based AI approaches. The first, which falls within the framework of AT\_Traveler, con-

cerns the personalization of the content of user interfaces [39] and the second, which falls within the framework of AT\_Freight (goods) carries on personalized route search based on CBR [40].

#### *Operation and traffic management*

Remember that “traffic operation and management” is one of the functional elements of the European rail system. Five types of AI applications are distinguished in this paragraph:

- Operation and management of traffic concerning “Passenger locomotives;”
- Operation and management of traffic concerning “freight wagons;”
- Operation and management of traffic concerning the “Metro;”
- Operation and traffic management concerning the European rail traffic management system: “ERTMS/ETCS;”
- Operation and traffic management regarding “train driving.”

Two studies were selected which are closely linked to the functional subsystem “Traffic Operation and Management”: (1) an expert system based on fuzzy logic for rail traffic control [41] and (2) the evaluation derailment accident risks based on the ensemble classification method [42]. The article by [41] describes an assistance system intended for use in railway operation control systems. It also contains expert knowledge of fuzzy rules of the “IF-THEN” type. Hundred rules were collected such as: “when the train delay is significant...” or “when the connection is important for many travellers...”, So...

The study by [42] on the assessment of train derailment accident risks is largely based on the use of artificial neural networks (ANN) and the ensemble classification method. Even if the work of [43] fits well into the framework of traffic operation and management, it will be developed with ontology-based methods later. This study aims at the ontological harmonization of information systems for rail freight transport (wagon) in Ukraine as opposed to the two previous studies which concern passenger locomotives [41, 42].

Based on historical rail accident reports reported by the National Transportation Safety Board, [44] proposed a case-based reasoning (CBR) approach for the analysis of risks related to the operation of the Metro. In this research, three main concepts relating to safety were considered by the authors: “precursors of accidents,” “safety risk” and “safety measures.” The basic idea is that subway systems with similar precursors tend to generate similar accidents. The dangerous events and safety measures produced by each historical case are recorded in a case database called “source cases” in CBR. Based on similarity measures between precursors and historical accident cases (source cases), the objective is to recover and possibly adapt similar accident cases to a new case (called target case in CBR) of which we seek the solution to the problem.

Still in the context of traffic operation and management, [45] also presented an approach to analysing the causes of metro operating accidents in China based on the a priori algorithm which is based on the search for association rules as well as on the theory of complex networks which is based on the

theory of graphs which are composed of nodes (or vertices) representing objects, interconnected by links (or edges). Recall that to define the properties of complex networks, we generally use three important concepts: the distribution of degrees (or probabilistic distribution), the average length of the paths, and the clustering coefficient (or coefficient of agglomeration or grouping or of aggregation) so the objective is to measure the grouping of nodes in a network. The clustering coefficient is the probability that two nodes are connected knowing that they have a neighbour in common.

In the work of [45], a database of 608 cases of metro operating accidents was developed. The proposed model was built based on 13 types of operational accidents, 29 causes and 84 relationships. The 13 types of metro accidents include collisions, derailments, fires, explosions, poisoning and suffocation, passengers falling on the rails, train doors closing, people being struck, stampede, flooding, operating delay, etc. To explore the safety risks of metro operation and provide suggestions for improving safety, five main steps were considered by the authors: (1) classification of metro accidents into 13 types, (2) search for causal factors based on historical accident cases and the experience of experts, (3) searches for potential association rules between the causal factors of accidents by applying the Apriori algorithm, (4) construction of the causal network of operating accidents of the metro based on the theory of complex networks (graph theory), (5) analyse topological characteristics and vulnerability linked to operational safety.

Two studies were selected which focus on the European rail traffic management system: “ERTMS/ETCS:” The development of an ontology to model ERTMS/ETCS [46] and the development of an ontology that considers the temporal aspect for ERTMS/ETCS [47].

A machine knowledge learning approach using CBR for automatic train driving was proposed in [48]. The initial case base (or source cases) contains 3624 cases collected from scenarios related to real train driving. To characterize a case, the following attributes were considered: applied/executed action (EAC), rail geometry (RG), initial kilometre (KM), number of locomotives (NL), number of wagons (NC), initial speed in km/h (IS), final speed (FS), maximum speed in km/h (MS), ramp percentage (%R) and total displacement (TD) in kilometres. Thus, each source case is described by the set of these attributes describing a driving problem with its own solution such as the acceleration point that the train driver must apply to the locomotive and the distance to maintain this defined point.

The objective of this research aims to reuse and/or adapt past experiences by helping the train driver to perform more efficient driving. To this end, two major steps are necessary. The first consists of recovering the cases most similar to the problem studied by using similarity measures; here the Euclidean distance was used. The second step focuses on adapting the most similar cases to the new situation. The authors use the 50 most similar cases as input to the adaptation process which is based on a genetic algorithm (GA) using certain driving rules, for example: the speed of the train after applying the new action must be less than the maximum authorized speed. Thus, the adaptation process provides an optimized solution to the new problem.

### Care/Maintenance

Several works based on AI and ontologies have been developed to improve the upkeep or maintenance of railway rolling stock [38, 49–55]

Li et al., [49] developed a machine learning approach for predictive maintenance and precisely to predict failures and alarms of critical railcar components. This study is based on the use of principal component analysis (PCA), support vector machine (SVM), linear classifier, decision tree and classification rules. Remember that support vector machines (SVM) are based on the use of machine learning algorithms to analyse data for classification and regression analysis. A linear classifier is a particular type of statistical classifier whose objective is to encrypt a decision by linear combination of samples which have similar properties, measured on observations. From the work of Quinlan in 1993, a decision tree is a decision support tool representing a set of choices in the graphic form of a tree and the possible decisions are located at the “leaves” of the tree. From the decision tree, we can generate classification rules. When we have a large dataset containing several variables, we seek not only to discover the most important variables, but also to reduce this dataset in order to represent it in a simple way. This is the main objective of principal component analysis (PCA) which constitutes one of the most frequently used methods of multivariate data analysis. It is often considered a data mining method because it makes it easy to extract information from large data sets. The data used as part of the work of [49] relating to predictive maintenance of wagons comes from historical data from detectors, failures, maintenance actions, inspection schedule, train type and weather data. The development of the decision support model includes five steps: feature extraction, dimension reduction, model training, confidence prediction and estimation, and finally rule simplification. Rules learned automatically from historical data can predict which railcars are most likely to have problems. Ref. [38] uses an expert system, machine learning (random forests and decision trees) and principal component analysis (PCA) to improve North American railcar maintenance planning decisions. Repair and inspection data were collected for four components of a specific railcar type from 1986 to 2020 from North American Railcar Owner (NARO) and the fleet selected for this study contains approximately 11,000 active railcars. Ref. [50] proposed a data-driven prioritization framework to mitigate the impact of maintenance on passengers during the operation of metro lines in Italy. Several AI approaches have been applied: the Markov chain Monte Carlo technique and machine learning, in particular the one-class support vector machine. Indeed, the proposed approach includes three steps:

- The Markov chain Monte Carlo approach to assess the criticality of assets based on the impact of their failure on passengers;
- A machine learning algorithm (one-class support vector machine) to group assets (i.e. functional, low degraded, medium degraded, highly degraded) based on their condition, based on data collected;
- A ranking algorithm is used to prioritize interventions.



A real case study was used regarding the M5 metro line in the Italian city of Milan (fully automated line). Passenger transportation demand data is collected by different systems, such as automated passenger counting (APC) systems and automated fare collection (AFC). Maintenance data includes both preventive and corrective maintenance interventions that are scheduled either immediately after the occurrence of a fault or during normal train operation. During this study, several categories of data and information were considered concerning track circuits, switches, platform doors, signalling equipment rooms and track antennas. The assessment of the condition of the assets (functional, slightly degraded, moderately degraded, severely degraded) was carried out using logs including several records.

The work of [51–54] is based in particular on the development of ontologies: Ref. [52] use the ontology to integrate railway condition monitoring data; ref. [53] proposed an ontology-based modelling approach for the predictive maintenance of railway subsystems. The ontology developed by [54] is based on the explicit and tacit knowledge of experts in the railway domain. Finally, [51] proposed an approach to support the management of rolling stock maintenance with a virtual depot based on ontology

Finally, a literature review on the applications of machine learning to railway maintenance is presented in [55].

#### *Safety in railway tunnels*

Recalling that certain learning methods improve the prediction of elaborate models but at the expense of a difficulty of interpretation and explanation in certain approaches, even the simplest ones, such as decision trees and linear regression models (least squares method), maximum likelihood model or even Bayesian inference) which generally seek to establish a linear relationship between a variable, called explained, and one or more variables, called explanatory (or predictive). Thus, in machine learning, the data is used to first train the algorithm on known (or labelled) data sets, then the learned model is used to predict unknown (unlabelled) values. SHAP (SHapley Additive exPlanations) is a technique for explaining and making understandable to humans the predictions of machine learning models. It is based on “Shapley” values, which use game theory whose objective is to quantify the predictive power of a model based on these characteristics. It is therefore statistical learning as opposed to symbolic learning. Thus interpretability, the objective of which is to improve a human’s understanding of a decision, today constitutes an important area of research in artificial intelligence.

In the field of railway tunnel safety, [4] proposed an interactive and explainable AI approach for railway tunnel construction which includes three AI techniques: machine learning, finite elements (FEM) and the Shapley Additive ExPlanations (SHAP) technique.

The explainable machine learning approach is based on building information modelling (BIM) with the aim of improving safety during tunnel construction and in particular mitigating the damage caused by the tunnelling of the Urban Metro. According to the authors, “*this approach allows designers to make*

*judgments about the most unfavourable ground conditions with the least accessible information about uncertainties when digging a tunnel*”. The proposed optimization approach was tested and simulated using pipeline (work) models based on simulation data from the finite element method and the SHAP technique.

However, the finite element method, which is generally based on partial differential equations as well as several calculation hypotheses, requires a good understanding of the different mathematical steps used during the approximation in order to estimate the error of the numerical model. in relation to the exact solution of the mathematical problem. Furthermore, the established numerical model only provides results relating to the information contained in the mathematical model that arises from the modelling assumptions.

### 6.1.3 | AI approaches related to both structural and functional elements of the rail system

In accordance with the regulations in particular Directive (EU) 2016/797 [2] of 11 May 2016 relating to the interoperability of the railway system within the European Union, the preceding paragraphs have classified AI approaches in the railway sector by distinguishing between functional and structural elements. However, certain AI applications, for example the management of route compatibility between rolling stock (vehicle) and infrastructure, fall within the framework of both structural and functionalities of the rail system. The approaches studied are based on the use of ontologies and knowledge graphs. Five ontology-based AI approaches whose objective is the management of route compatibility: [56–60]. Involving both the structural and functional elements of the railway system, these approaches will be presented in the paragraph dedicated to methods based on ontology and knowledge graph.

### 6.1.4 | AI approaches related to rail safety

Remember that the list of safety requirements from Directive (EU) 2016/798 concerns essential requirements, safety-related requirements, national reference values (NRV), common safety objectives (CSO), common safety indicators (CSI), the safety certificate, the safety approval, the safety management system (SMS), the common safety methods (CSM) for risk assessment, the realization of the CSOs, the SMS control, monitoring, safety integration, safety-critical (or essential) tasks, change management (modifications) and accident and incident investigation. Unfortunately, the AI applications analysed do not actually and explicitly address these safety requirements necessary for subsystem design, development, SMS risk management, safety control and monitoring the safety of the European rail system. However, several applications can be classified as part of the feedback process and therefore after the operation of the system. We have classified these AI applications into two categories: 1) analysis of railway accidents based on *investigation reports* and 2) analysis of railway accidents based on *manufacturer files*.

### *Analysis of railway accidents based on investigation reports*

This paragraph presents the following works: [5, 49, 61–66] and Awad et al. [67].

Ref. [61] used case-based reasoning (CBR) and rule-based reasoning (RBR) for railway incident prevention. Ref. [62] applied data mining techniques and precisely association rules (Clementine 12. software) to analyse data related to Iranian Railway Accidents (RAI). This research was carried out using 6500 accident records from an accident database from 1996 to 2005. The relationships discovered between the most common accident factors such as human errors help prevent the reproduction of some accidents in the future. This study made it possible, according to the authors, to define safety rules and regulations in three areas linked to human resources, railway tracks and wagons.

The text mining approach using random forests and latent Dirichlet allocation (LDA) were implemented by Brown [66] to contribute to the analysis of railway accidents. Random forests (or forests of decision trees) are part of decision tree learning techniques which are decision support tools whose objective is to represent different possible decisions in the form of a graphical tree. As for the unsupervised learning algorithm (Latent Dirichlet Allocation or Latent Dirichlet Allocation: LDA), which is part of natural language processing (NLP) techniques, it constitutes a probabilistic model making it possible to explain sets of observations using data similarity measures.

The objective of Brown's work (2016) aims to use these data mining techniques in the form of accident narrative texts with a view to automatically discovering the characteristics and particularities of rail accidents in the United States. The data used comes from accidents over the 11 years from 2001 to 2012 archived in annual accident reports.

Based on around a hundred urban rail transportation accident reports collected from the National Work Safety Administration, [49] also proposed a text mining method for analysis of railway accident reports and thus identify participants and safety risk factors. The “K-means” classification algorithm of the ROST software was used to establish the descriptive model of accidents making it possible to identify and classify keywords such as, for example, underground pipeline, elimination of hidden dangers, protection of the enclosure, violation of work regulations, hydro geological condition, construction monitoring, timely communication, safety measures, personnel training, construction management plan, etc.

Still within the framework of data exploration and in order to reveal the presence of informative concepts on causes and failures such as human or technical causes, [63] studied the potential interest of natural language processing (NLP) for the analysis of UK rail accident data from rail accident and incident investigation reports.

To compare approaches to exploring and mining texts relating to railway accidents from investigation reports in the United States, ref. [5] used two techniques: latent semantic analysis (LSA) and latent Dirichlet allocation (LDA). LSA, also called latent semantic indexing (natural language processing technique), uses a matrix describing the occurrence of certain terms

(words) in documents. The occurrence matrix is then transformed to find the relationships between terms and concepts and between these concepts and the analysed documents. LDA, for its part, also from the field of natural language processing, is a probabilistic model making it possible to explain sets of observations based on measurements of data similarities. Finally, the accidents identified are shunting accidents, accidents in marshalling yards and accidents at level crossings.

Still within the framework of data mining techniques and with a view to predicting the risks of railway derailment accidents, [64] used an ensemble classifier which combines the prediction results of each classifier by a weighted average method. Three data mining techniques were used: artificial neural networks (ANN), the “Naïve Bayes” classifier, and the decision tree. Thus, three probabilistic prediction models were developed. To make the final decision regarding derailment accident risk assessment, the output of each model is given a weighting based on its prediction accuracy using a genetic algorithm (GA). To validate the effectiveness of the model, this approach was applied to data from the Islamic Republic of Iran (RAI) railway. The objective of this study is to discover significant patterns and trends among Iranian railway derailment accident data

Text mining is also used in [65] to discover the causes of accidents from investigation reports. The implemented approach uses three deep learning techniques: convolutional neural networks (CNN), recurrent neural networks (RNN) and deep neural networks (DNN). The data comes from Federal Railroad Administration (FRA) reports and collected over 17 years (2001–2017). Thus 40,164 reports were examined with five categories of major accidents. According to the authors, the ten main causes identified show that the deep learning approaches applied make it possible to correctly classify the cause of a railway accident.

To predict the annual number of injuries in urban rail transport [67], also used artificial neural networks. In this study, two models were developed. Using a dataset comprising 22 URT systems from the years 2010 to 2019, the first model aims to examine the relationship between safety incidents and the injury rate per million passenger trips. From a second dataset comprising 31 URT systems from 2013 to 2019, the second model aims to examine the relationships between the operational characteristics of the system and the number of injuries. Using the parameters estimated in the second model, it was possible to develop a formula for predicting the annual number of injuries. Thus, these two models make it possible to identify the main railway incidents and to understand the relationships between the different operational characteristics of the system and its safety performance. This approach, based on artificial neural networks, was applied to a set of data from 31 railway systems. The data comes from the Community of Metros (COMET), a global urban rail benchmarking group run by the Transport Strategy Center (TSC) at Imperial College London.

### *Analysis of railway accidents based on manufacturer files*

Previous approaches that leverage rail accident data from rail accident and incident investigation reports often use data

mining (or text mining) techniques to analyse accident-related data, discover the causes of accidents, predict the risks of railway accidents, reveal the presence of informative concepts on the causes of accidents and incidents, identify the actors and risk factors for safety, discover relationships between the factors of common accidents such as human errors, distinguishing the characteristics and particularities of accidents, properly classifying the cause of an accident, discovering significant patterns and trends in accident data or even predicting the annual number of transportation injuries railway. Other approaches use not investigation reports but rather the files of manufacturers and rail safety experts with a view to improving rail safety. However, in both cases, the data comes from feedback. The first approaches use the feedback contained in the investigation reports and in this case the rail system is already operational and has received its operating authorization from the safety authorities. On the contrary, in the case of safety analyses which is based on the files of system designers and the know-how of safety experts, the objective of the safety studies relates to the design and development of the system before it is put into service. The work presented in [68–73] is part of this second orientation. More precisely, these are analysing of the dangers linked to critical software and functional safety analyses which are integrated from the specification and design phases of the system, the objective of which is to prevent the occurrence of railway accidents and the seriousness of the damage caused well before the operation of the system. In order to guarantee an acceptable level of risk with regard to man, the system and its environment, railway safety experts use several safety analysis methods: Preliminary risk analysis (PHA), functional safety analysis (FSA), failure modes, effects and criticality analysis (FMECA), software error effects analysis (SEEA), fault tree analysis (FTA), etc. The PHA aims to identify potential accidents linked to the transport system and its interfaces in order to evaluate and propose solutions to eliminate reduce or control them. The FSA focuses on justifying that the system design architecture is safe against potential accidents identified by the PHA and therefore ensuring that all safety provisions are considered to cover potential hazards or accidents. Such analyses provide (low-level) safety criteria for system design and the creation of hardware and software safety equipment. They also impose safety criteria linked to the dimensioning, operation and maintenance of the rail system. An FSA can highlight dangerous scenarios that require improvement and rectification in the specification and design phases of the transportation system.

Hadj-Mabrouk work falls within the framework of two safety analyses: Functional safety analysis (FSA) and software error effects analysis (SEEA). In order to rationalize the traditional FSA method, improve the quality of accident risk analyses and therefore help experts to judge the completeness of an FSA and the adequacy of the protection measures considered, the proposed approach is based on several aspects of AI and in particular on the use of the following techniques [68, 70, 71]:

- A knowledge acquisition phase to gather data on functional safety in the form of potential accident scenarios from the

files of manufacturers of the rail transport system and the experience and know-how of experts in the field of safety;

- A learning phase by classification of concepts to group accident scenarios into homogeneous classes, for example accidents linked to collisions or train derailments;
- A rule-based machine learning (RBML) phase to identify, from the basis of historical scenarios, the relevant safety rules, often difficult to extract manually from safety experts;
- A knowledge-based system (or expert system) to which the production rules, previously deduced by machine learning, are transferred to build the knowledge base of the functional safety assessment tool (FSA) and consequently infer and deduce, by forward chaining, potential dangers not considered in the rail system design files.

In the context of software safety analysis, [69] proposed a decision support system based on case-based reasoning (CBR) to help experts in safety to judge the completeness and consistency of the analysis of the effects of software errors (Software Error Effect Analysis—SEEA). The objective of this study is to exploit a case base consisting of historical SEEA (source case), carried out on already validated and certified software, in order to explain or evaluate a new case of SEEA for a new software safety (target case) and consequently help and stimulate the imagination of safety experts in the search for new critical situations contrary to safety which require the implementation of barriers or safety instructions and adequate preventive measures. To demonstrate the feasibility of the proposed approach, the author presented an application example based on 224 SEEA cases from the knowledge acquisition phase of rail transport systems already certified and put into service in France.

## 6.2 | AI approach based on ontology and knowledge graphs in rail transport

Several “classic” AI techniques (presented above) are implemented in particular machine learning (supervised, semi-supervised, unsupervised), deep learning such as artificial neural networks (ANN), natural language processing (NLP), case-based reasoning (CBR). However, the lack of interoperability between AI tools often based on different modes of knowledge representation, the difficulty of structuring knowledge in a field, the insufficiency of these approaches to bring together and capitalize on knowledge bases and the inability to share and reuse this knowledge have motivated and directed research towards the development of new approaches based on ontology and knowledge graphs. These new approaches, based essentially on a formal representation of knowledge and considering the interoperability and reusability of this knowledge, have experienced significant growth in recent years in the railway sector. This study shows that ontology and knowledge graphs will certainly have a greater impact on the field of rail transport safety and in particular on the management and prevention of rail accident risks.



## 6.2.1 | Ontology-based approaches

Data integration in the railway domain based on ontology was proposed in [56]. The authors developed an ontology-based methodological framework called “Network Statement Checker” which draws on an infrastructure database describing the railway network. This ontology integrates network declarations from different countries into a single information model to determine whether a given route can be used, from a compatibility perspective. The user of the tool can select a route on the European railway map and find information on the characteristics of each track section of a route. The results of this study were evaluated using a demonstrator developed as part of a European research project called InteGRail (Intelligent Integration of Railway Systems [74]). Indeed, to resolve the problem of compatibility of European rail routes and in the context of Directive (EU) 2016/797 [2] relating to the interoperability of the rail system of the European Union, the European project InteGRail was financed by the Commission European Union which brings together 39 stakeholders representing the main players in the railway industry. InteGRail aimed to strengthen the sharing of information between infrastructure managers (IM) and railway undertakings (RU) and is based in particular on the “Network Statement Checker” ontology presented above.

Rail interoperability often refers to the ability of the rail system to operate trains safely and seamlessly on different rail networks located in different Member States. Under Commission Implementing Regulation (EU) 2019/777 of 16 May 2019 on common specifications for the railway infrastructure register, the European Infrastructure Register (RINF) makes it possible to define the characteristics of the railway network European by providing the main parameters to be used to check the technical compatibility between the vehicle and the route.

Based on the requirements linked to the European Infrastructure Register (RINF) which are imposed by Directive (EU) 2016/797 [2] of 11 May 2016 relating to the interoperability of the railway system within the European Union, [57] proposed a tool based on the ontology called “RaCoOn” making it possible to give for example the (approximate) location of the train based on the known positions of the track circuit. Infrastructure and location data are stored and used as the basis for modelling train movements. Track circuits were added manually, using simulated track circuit distances. Finally, a demonstrator for validating this principle was presented, based on a new ontology of the railway domain created at the University of Birmingham. In the same context and in the field of railway infrastructure, [75] presented the RAISO approach (RAilway Infrastructures and Signalling Ontology) which is based on a railway signalling ontology making it possible to formalize the route of a railway network including the position of track elements (signals, train detector etc.). Ref. [76] also developed a railway infrastructure topology ontology to represent infrastructure characteristics in accordance with domain standards. In the context of urban freight transport systems, [40] proposed a personalized route search approach based on both ontology and case-based reasoning (CBR). The route retrieval mechanism uses CBR to extract city traffic information and provide the user with an optimal

route. In the field of railway control, command and signalling, Ref. [46] proposed an ontology with a view to modelling the European rail traffic management system (ERTMS) and in particular the ETCS (European Train Control System). Ref. [47] also proposed a railway ontology to take into consideration the temporal aspect in the ERTMS/ETCS ontology. To consider user needs, [39] proposed a transport ontology allowing the personalization of user interface content. The concepts used are for example Calendar, City, Connection link, Connection point, Interchange hub, Journey, Operator, Railway element, Railway junction, Road element, Crossing, Stopping point. To support performance monitoring in public transport systems, [77] developed an approach based on an ontological representation. Key performance indicators (KPIs) considered include, for example, actual dwell time, scheduled dwell time, advanced dwell time and average lead time/advance. Ref. [78] established an ontology of railway equipment malfunctions based on terminology (extracted from standards) such as dangers, causes, effects and safety measures. The idea of considering dysfunctions is very important but requires more modelling. This is a high-level ontology that requires the in-depth instantiation of knowledge from the railway safety domain. The work of [43] aims at the ontological harmonization of railway freight transport information systems in Ukraine and in particular the automated freight traffic control system.

In the field of railway accidents, [79] proposed an approach to construct ontologies of the railway domain and in particular processes accident data relating to the derailment of a train, as for [80, 81] their approach to helping model railway accident scenarios is based on two complementary ontologies: (1) a generic ontology which brings together high-level concepts involved in railway safety such as context, dangerous elements, events dangerous, the causes of the accident and (2) an ontology of the domain centred on the railway system, the human operator and the environment. The concepts involved in the domain ontology are specializations of other concepts of the generic ontology. This is a feasibility study focused on rail collisions with a view to better formalizing and structuring the knowledge involved in rail accident scenarios. Still in the context of modelling railway accident scenarios, [82] developed an approach based jointly on ontology and machine learning whose objective is the prevention of potential accidents. The proposed example of ontology formalizes accident scenarios according to four dimensions: (1) symptoms (general context of the scenario, potential accidents, level of risk); (2) causes (system, human factors, environment, and interactions); (3) potential dangers and (4) safety measures adopted (protective measures and preventive measures).

In the field of railway maintenance, several works based on ontology have been developed. Ref. [52] used the ontology to integrate railway condition monitoring data; [53] developed an ontology-based modelling approach to perform predictive maintenance operations on railway subsystems; [54] developed several conceptual models based on ontologies to improve railway maintenance. By exploring explicit and tacit knowledge from domain experts, [83] also developed ontology to manage railway maintenance. Finally, [51] proposed an approach to support the management of rolling stock maintenance with a



virtual depot based on ontology. In the context of autonomous driving, [84] proposed the ontology called ATMO intended for autonomous trains.

Considering the importance of ontologies in the transportation sector, [85] presented a survey of existing ontologies in the field of land transportation by examining several characteristics of the developed ontologies such as precision, generality, granularity, the competence. Several ontologies are examined in this study which focuses mainly on road safety:

- Road accident ontology to capture accidents and their relevant information;
- Road traffic management ontology to provide decision support to drivers;
- Transport ontology for personalizing information for travellers (presented above);
- Ontology of transport disruptions;
- iCity ontology to capture data collected and generated on the urban system;
- Network statement checker ontology to check the feasibility of running a train on a given track (presented above).

According to [85], data in land transportation comes from different organizations, sensors, surveys and is varied, complex and published in different formats, with different granularities and with different and sometimes ambiguous properties. There is no single ontology covering all concepts relevant to transportation research. No single ontology captures the entire high-level transportation taxonomy. Ref. [86] carried out an inventory of systems engineering based on ontologies, considering in particular product systems (concurrent engineering), service systems, business systems and the ISO standard /IEC/IEEE 15288. The authors provide important insights related to systems engineering by successively examining the knowledge areas supported, the contribution of existing ontologies and the techniques adopted. Emphasis is placed on the main advantages of ontology in terms of interoperability, communication, explicitness, reusability of knowledge, homogeneous terminology to eliminate inconsistencies, unified vocabulary, controlled semantics, common understanding of a domain and reasoning on logical axioms [86].

#### *Ontologies for the harmonization of risk management standards*

The objective of the work of [87] aims at the harmonization of standards, in particular the ISO 27001 and ISO 20000 standards. This study is essentially based on the implementation of an ontology providing a vocabulary, terms, concepts and specialized relationships in harmonizing multiple models. The objective is to eliminate inconsistencies, confusion and terminological conflicts at the different hierarchical levels and therefore propose precise definitions, a simple representation of processes and a uniform and formal vocabulary. This article describes an ontology that provides consistent terminology to support the harmonization of multiple models. In this same context of harmonization of standards, [88] proposed an ontology to support the implementation of ISO standards relating to risk management with a view to facilitating the choice of

risk management techniques most appropriate to the needs of a specific risk management activity. The objective of this ontology is to support the implementation of ISO standards on hazard identification, analysis and risk assessment. For this purpose, several ISO standards were examined: ISO 31000 (Risk management – Principles and guidelines), ISO 31010 (Risk management – Risk assessment techniques) and ISO 73 (Risk management – Vocabulary). Using the “Protégé” tool, the authors have developed an ontology called “OntologyRATIS” which brings together the basic concepts extracted from the ISO 31010 document. In order to facilitate the choice of risk management techniques best suited to the needs, the ontology can be questioned through general questions, such as: “What methods are used for risk identification?” For a risk analysis? For the evaluation? Which methods provide quantitative results? Or qualitative? According to [89], the semantics of terms used in international standards (ISO) can often be contradictory, or at best misaligned, between pairs of standards with similar objectives. The authors showed how conceptual modelling and ontology engineering can be effective in reconciling variation in disparate standards, particularly engineering standards. The objective is to study the potential usefulness of ontologies for streamlining the suite of international software engineering standards. In this context of harmonization of ISO standards, the authors identified five areas in which ontologies could be useful: (1) the definitional area often called fundamental ontologies or higher-level ontologies; (2) the modelling domain; and (3) the domain of practice. Building on the work of [89, 90], a project was initiated within the framework of ISO/IEC, the objective of which is to provide a shared ontology for SC7 standards. According to the authors, software engineering standards often use different underlying metamodels and ontologies, which sometimes differ from one standard to another. To this end, the harmonization of these standards through the use of domain ontology was created from existing ISO/IEC standards, in particular ISO/IEC 24744 and 24765 which is based in particular on the ontology of definitional elements (DEO) and the configured definitional ontology (CDO).

#### 6.2.2 | Approaches based on knowledge graphs

In recent years, several works focused on knowledge graphs have been developed to improve the safety of rail transport.

Based on railway accident investigation reports (published on the UK RAIB website), [91] proposed a knowledge graph-based approach to explore the causes of railway operational accidents. In the framework of railway accident causality networks, nodes represent accidents and/or their causal factors, for example, hazards and the edges connecting the nodes represent the relationships between the nodes. In the field of maintenance of railway rolling stock and based on the fault tree method [92] proposed an approach to construct a knowledge graph with a view to assisting the maintenance technician maintenance in its task of researching the causes and remedies for failures (or breakdowns) of rolling stock. Based on “FAR” accident data from

American railways, [93] proposed a knowledge graph based on ontology with a view to identifying, preventing and controlling the main points of risk as well as the risk paths of railway fire accidents. The study proposed by [94] concerns the development of a knowledge graph with a view to modelling the correlations between the dangers linked to rail accidents in the United Kingdom covering a decade. In the context of the construction of railway bridges, [95] developed a method for the dynamic updating of a knowledge graph based on multi-source data in the bridge construction process. The authors propose a scientific basis necessary for bridge management and thus help to improve the level of management of bridge computerization. To prevent railway operating accidents, [96] proposed an interesting hazard prediction approach based on knowledge graphs. This approach to modelling railway operating accidents called ROAKG made it possible to identify the main lessons:

- Missing or late deceleration applied by a train driver;
- Error of assessment of the current dangerous situation;
- Deterioration or damage to rolling stock including bogies and wheels;
- Failure of a signalling system or equipment.

Several other approaches to preventing railway dangers and accidents are presented in [96] in particular the distribution of freight rail accidents in Canada from 1995 to 2015 according to fatigue, the distribution of accidents at railway crossings level in the United States between 2009 and 2014, the distribution of the severity of railway accidents in the United States from 2000 to 2016 according to the types of accidents, the study of the frequency of fatal accidents according to different types of level crossings, the evaluation of the frequency of freight train derailments, the study of the frequency of 407 accidents/incidents which led to the most important cause, namely human error, the study of the relationships between human errors and types of railway accidents. In accordance with European regulations on the interoperability of European rail systems, it is mandatory to check the compatibility of routes between the European rail network managed by infrastructure managers and the vehicles for which the railway undertakings are responsible. In 2020, and in order to check the compatibility of routes, the European Union Agency for Railways (Agency) developed a knowledge graph which is based in particular on data from two European registers: the European Register of infrastructures (RINF) and the European Register of Authorized Type Vehicles (ERATV). The knowledge graph covers 27 European countries and describes more than 2000 vehicle types, 270,000 track segments and 50,000 stations [60]. According to [58], the verification of route compatibility is based in particular on: (i) An ontology of the railway infrastructure and the types of authorized vehicles, (ii) a knowledge graph describing the railway infrastructure European; (iii) a system architecture for use case development; and (iv) an open source, native RDF (Resource Description Framework) web application to support route compatibility checks. Ref. [59] also proposed a knowledge graph for checking the compatibility of routes. The objective is to exploit the terminological harmonization achieved in railway

legal documents by developing a reference vocabulary based on a reusable knowledge graph that can be used by railway stakeholders and thus improve the interoperability of railway data. The interest and importance of knowledge graphs as tools for explainable machine learning are studied through a detailed investigation in [97]. The need to improve interpretability and explainability in machine learning systems and in particular deep learning, often considered as black boxes that are difficult to verify and interpret, has directed researchers towards the development of approaches, techniques and tools allowing explainable learning. According to the authors, knowledge graphs, which naturally provide basic domain knowledge in a machine-readable format, could be integrated into explainable machine learning approaches to provide meaningful explanations and thus improve the interpretability and reliability from the user's point of view. Indeed, semantic approaches and symbolic representations in the form of ontologies and knowledge graphs make it possible to structure, represent and capture knowledge and data in the domain.

## 7 | SUMMARY OF AI APPLICATIONS IN RAIL TRANSPORT AND CLASSIFICATION ACCORDING TO EUROPEAN REGULATIONS

This bibliographic study presented an overview (which does not claim to be exhaustive) of AI applications involved in the rail transport sector with a particular emphasis on approaches related to rail safety. To this end, several summaries have been proposed:

1. List of subsystems, equipment and constituents involved in AI applications;
2. Distribution of AI methods and algorithms between structural elements, functional elements and approaches related to railway safety;
3. Distribution of AI approaches studied by type of equipment:
  - Summary of AI methods involved in structural elements;
  - Summary of AI methods involved in the functional elements;
  - Summary of AI methods involved in both structural and functional elements;
4. Distribution of AI approaches involved in railway safety:
  - Summary of AI applications involved in the analysis of railway accidents based on investigation reports;
  - Summary of AI applications involved in the prevention of railway accidents based on manufacturer files;
  - Summary of AI applications involved in the harmonization of ISO standards;
  - Summary of ontology-based AI applications;
  - Summary of AI applications based on knowledge graphs.

Table 3 presents a summary of this literature review on the applications of AI in the field of rail transport safety. What to remember from these summaries on the application of AI to rail transport:

**TABLE 3** Summary of the literature review on AI applications in the field of rail transport safety.

System	Subsystems	Equipment/ Constituents	AI methods and algorithms	Objectives
Structural elements	Infrastructure	<ul style="list-style-type: none"> <li>– Railway tracks (Ballast)</li> <li>– Railway tracks (Rails)</li> <li>– Railway tracks (Track geometry)</li> <li>– Track devices (Switch system)</li> <li>– Levelcrossing</li> <li>– Infrastructure</li> </ul>	<ul style="list-style-type: none"> <li>– Learning by back propagation of the gradient</li> <li>– Deep learning that uses neural networks</li> <li>– Ontology</li> <li>– Multilayer perceptron (artificial neural network organized in several layers)</li> <li>– Case-based reasoning (CBR)</li> <li>– Support vector regression (SVR)</li> <li>– Petri net</li> <li>– Long-term and short-term memory (LSTM) neural network</li> <li>– Convolutional Neural Network (CNN)</li> <li>– Convolutional Neural Networks (CNN)</li> <li>– Artificial neural networks</li> <li>– Deep Convolutional Neural Networks (DCNN)</li> <li>– ELMAN Recurrent Neural Networks</li> <li>– Expert system</li> <li>– Natural Language Processing (NLP)</li> </ul>	<ul style="list-style-type: none"> <li>– Analysis of the dangers linked to accidents at level crossings</li> <li>– Detection of rail surface defects</li> <li>– Diagnosis of switching system faults</li> <li>– Inspection of rail surface defects</li> <li>– Railway track inspection</li> <li>– Maintenance of railway ballast</li> <li>– Railway infrastructure topology ontology</li> <li>– Prediction of change in railway track geometry</li> <li>– Forecasting breakdowns on railway tracks</li> </ul>
	Rolling stock	<ul style="list-style-type: none"> <li>– Locomotive (Vehicle)/Running parts/Axle</li> <li>– Locomotive (Vehicle)/Running gear/ Wheels</li> <li>– Locomotive (Vehicle)</li> <li>– Wagons (Goods)</li> </ul>	<ul style="list-style-type: none"> <li>– Decision trees</li> <li>– Principal component analysis (PCA)</li> <li>– Expert system</li> <li>– Digital twin based on machine learning</li> <li>– Fuzzy logic</li> <li>– Statistical analysis methods (Standard deviation, Regression, Hypothesis testing)</li> <li>– Case-based reasoning (CBR)</li> <li>– Artificial Neural Network (ANN)</li> <li>– Deep Belief Network (DBN)</li> <li>– Short Term Fourier Transform (STFT)</li> <li>– Non-negative matrix factorization (NMF)</li> <li>– One-class support vector machine (OC-SVM)</li> <li>– Multi-layer perceptron autoencoder (MLP-AE)</li> <li>– Convolutional Neural Network Autoencoder (CNN-AE)</li> </ul>	<ul style="list-style-type: none"> <li>– Diagnosis and detection of defects for the maintenance of “Axles”</li> <li>– Diagnosis and detection of defects for the maintenance of “Wheels”</li> <li>– Diagnosis and prediction of breakdowns for the maintenance of “Locomotive”</li> <li>– Diagnosis and prediction of breakdowns for the maintenance of “Wagons”</li> </ul>
	Energy	Traction equipment (Pantograph)	Learning based on automatic classification	Diagnosis and prediction of breakdowns for the maintenance of “Pantographs”
Functional elements	Telematics applications (TA)	<ul style="list-style-type: none"> <li>TA freight</li> <li>TA Voyageurs</li> </ul>	<ul style="list-style-type: none"> <li>– Ontology</li> <li>– Case-based reasoning (CBR)</li> </ul>	<ul style="list-style-type: none"> <li>– Ontology for customizing user interfaces</li> <li>– Ontology for searching personalized routes</li> <li>– Ontology to evaluate key performance indicators</li> </ul>
	Care/Maintenance	<ul style="list-style-type: none"> <li>– Rolling stock/ Wagons</li> <li>– Rolling stock/Metro</li> <li>– Rolling stock</li> </ul>	<ul style="list-style-type: none"> <li>– Ontology</li> <li>– Expert system</li> <li>– Principal component analysis (PCA)</li> <li>– Support vector machine (SVM)</li> <li>– Decision tree, Random forests and Classification rules</li> <li>– Linear classifier</li> <li>– Monte Carlo technique by Markov chain</li> </ul>	Maintenance and monitoring of railway rolling stock (Locomotive, Wagon, Metro)
	Operation and traffic management	<ul style="list-style-type: none"> <li>– Locomotive</li> <li>– Wagons</li> <li>– ERTMS/ETCS</li> <li>– Metro</li> <li>– Trains</li> </ul>	<ul style="list-style-type: none"> <li>– Expert system</li> <li>– Ontology</li> <li>– Fuzzy logic</li> <li>– Case-based reasoning (CBR)</li> <li>– Association rules (a priori algorithm)</li> <li>– Theory of complex networks (graph theory)</li> <li>– Artificial neural networks (ANN)</li> </ul>	<ul style="list-style-type: none"> <li>– Rail traffic control</li> <li>– Ontology to model ERTMS/ETCS</li> <li>– Driving assistance for the train driver</li> <li>– Analysis of the causes of metro operating accidents</li> <li>– Analysis of operational risks</li> <li>– Assessment of derailment accident risks</li> <li>– Harmonization of freight transport information systems</li> </ul>

(Continues)

TABLE 3 (Continued)

System	Subsystems	Equipment/ Constituents	AI methods and algorithms	Objectives
Structural and functional elements	Safety in railway tunnels	Tunnels	<ul style="list-style-type: none"> <li>- Machine learning,</li> <li>- Finite element method (FEM)</li> <li>- Shapley Additive ExPlanations (SHAP)</li> </ul>	Detection of damage caused by the digging of Metro tunnels
	Infrastructure and rolling stock	Rail system	<ul style="list-style-type: none"> <li>- Ontology</li> <li>- Knowledge graph</li> </ul>	Route Compatibility Check
Rail safety	Autonomous train	Autonomous train	Ontology	Autonomous train card ATMO ontology
	Analysis of accidents based on investigation reports	Rail system	<ul style="list-style-type: none"> <li>- Natural language processing (NLP)</li> <li>- Latent Dirichlet Allocation (LDA)</li> <li>- Latent Dirichlet Allocation (LDA)</li> <li>- Random forests (or decision tree forests)</li> <li>- K-means</li> <li>- Case-based reasoning (CBR)</li> <li>- Rule-based reasoning (RBR)</li> <li>- Association rules (Clementine software)</li> <li>- Artificial neural networks (ANN)</li> <li>- Convolutional neural networks (CNN)</li> <li>- Deep neural networks (DNN)</li> <li>- Recurrent neural networks (RNN)</li> <li>- Social network theory</li> </ul>	<ul style="list-style-type: none"> <li>- Data mining and analysis of railway accidents</li> <li>- Analysis of railway accident stories</li> <li>- Predict the annual number of injuries</li> </ul>
	Accident prevention based on manufacturer files	Rail system	<ul style="list-style-type: none"> <li>- Learning by classification</li> <li>- Learning production rules</li> <li>- Expert system</li> <li>- Case-based reasoning (CBR)</li> <li>- Ontology</li> </ul>	<ul style="list-style-type: none"> <li>- Analysis and prevention of accident risks linked to functional safety;</li> <li>- Analysis and prevention of accident risks linked to software safety.</li> </ul>
	Accident prevention based on railway standards	Rail system	Ontology	Analysis of dysfunctions in the design of railway systems
Literature review	Harmonization of standards	ISO standards	Ontology	Ontology for ISO standards
	Railway track maintenance	Rail system	Apprentissage automatique	Applications of machine learning in railway maintenance [55]
	Ontologies in land transport	Land transportation	Ontologie	A survey of ontologies in the field of land transportation [85]
	Ontology-based systems engineering	Systems engineering	Ontologie	State of the art on ontology-based systems engineering [86]

- The structural elements of the rail system involved are infrastructure, rolling stock and energy;
- AI applications relating to infrastructure concern track devices (connections or switch systems), railway tracks (rails, ballast, track geometry) and level crossings (PN);
- The functional elements concern telematics applications (passengers and goods), traffic operation and management (locomotive, freight wagon, metro, train, European rail traffic management system: ERTMS/ETCS), maintenance and maintenance (wagons, metro, tunnel) and finally safety in railway tunnels;
- Some applications involve both structural and functional elements and relate to infrastructure and rolling stock (vehicle). All these applications are dedicated to establishing and checking the compatibility of routes, particularly from the infrastructure register and the vehicle or vehicle type register;
- AI applications linked to the safety of the railway system concern the harmonization of ISO standards, the analysis of railway accidents based on investigation reports (feedback) after the commissioning and operation of the railway system and finally the prevention of railway accidents from manufacturers' files well before the operation of the system, but rather during the specification and design phases of the system. It is for this reason that a distinction was established between the prevention of accidents in this second case as opposed to the analysis and understanding of the causes of accidents in the case of feedback.
- The AI methods and algorithms are distributed in Table 3 according to this equipment, these constituents and these security approaches.
- Deep learning plays an important role: Long-term and short-term memory (LSTM) neural network, artificial



neural networks (ANN), convolutional neural networks (CNN), deep convolutional neural networks (DCNN), deep neural networks (DNN), recurrent neural networks (RNN), deep belief network (DBN), multilayer perceptron trained with the BFGS algorithm, multi-layer perceptron autoencoder (MLP-AE), convolutional neural network autoencoder (CNN-AE).

- Only an application that integrates the explainability problem in AI using Shapley Additive ExPlanations (SHAP) which is a way to explain the output of machine learning models.
- Ontology and knowledge graphs have been used in particular to solve problems related to railway safety.
- Latent semantic analysis (LSA) and latent Dirichlet allocation (LDA) have been used for natural language processing (NLP).
- Several applications use case-based reasoning (CBR) to search for similar or analogous solutions from a base of source cases.
- To discover interesting relationships between variables stored in databases, several researchers have used association rules, in particular the a priori algorithm and the Clementine software.
- One-class support vector machine (OC-SVM) is often used for discrimination and regression problems. While support vector machines (SVR) is implemented for classification and regression analysis.
- Several statistical data analysis methods like statistical mean, standard deviation, regression, hypothesis testing, principal component analysis (PCA) and non-negative matrix factorization (NMF) as an algorithm in analysis multivariate and linear algebra have been commonly used.
- Several approaches have also been used to solve grouping, discrimination and classification problems, in particular the linear classifier (statistical classification), K-means (combinatorial optimization), decision trees (random forests), classification rules, back propagation learning (MLP) or gradient back propagation.
- Finally, the expert system, the learning of production rules, fuzzy logic, the theory of complex networks (graph theory), the Monte Carlo technique by Markov chain, the theory of social networks, the Fourier transform short term (STFT), the finite element method (FEM), the digital twin (based on learning) and the Petri net are also used for decision support.

## 8 | POSITIONING OF THE STUDY IN RELATION TO RAILWAY REGULATIONS

Table 4 summarizes all the works studied by distinguishing the list of railway subsystems, equipment and the objectives of the AI and machine learning approaches. 65 articles are examined, of which 61% of the documents concern subsystems of a “structural” and “functional” nature, 26% are related to the safety of the railway system and finally 6% concern the harmonization of standards:

- Structural elements: 32% of the documents are devoted to “structural elements” (rolling stock and infrastructure). The “structural” elements of the European railway system are

infrastructure, rolling stock and energy. AI applications relating to “rolling stock” concern the following equipment: Axle, wheels, ballast, rails, switch system, track geometry, locomotive, wagons. They have two main objectives: (1) diagnosis, fault detection and failure prediction and (2) inspection and maintenance of rolling stock. As for the work dedicated to “infrastructure,” it focuses either on analysing the dangers related to accidents at level crossings (LC), or on developing ontologies describing the topology of the infrastructure. Only one application concerns the “Energy” subsystem and more precisely the “Pantograph” whose objective is to identify the dangers related to defective pantographs.

- Functional elements: 32% of the documents are also devoted to “functional elements” which involve telematics applications, operation and traffic management (locomotive, wagon, metro, train and ERTMS/ETCS), maintenance (wagons, metro, tunnel) and finally safety in railway tunnels. The “telematics applications” intended for passengers and goods are focused on developing ontologies for (1) customizing user interfaces, (2) searching for personalized routes and (3) evaluating key performance indicators. AI applications related to “operation and traffic management” aim at: (1) analysis and assessment of risks related to operation, (2) driving assistance for the train driver, (3) control of rail traffic, (4) modelling of the ERTMS/ETCS system based on ontology and (5) harmonization of rail freight transport information systems. AI applications related to the “Maintenance/Maintenance” functional subsystem mainly concern the maintenance of rolling stock and in particular the maintenance of freight wagons. Studies related to “tunnel safety” concern the identification and prevention of hazards during the construction of railway tunnels.
- Structural and functional elements: 9% of the documents concern both “structural and functional elements” (infrastructure and rolling stock) and are mainly interested in establishing “route compatibility” from infrastructure registers and vehicle or vehicle type registers. All these applications are based on the use of ontologies and knowledge graphs.
- Railway safety: 26% of the documents are devoted to the “safety” of the railway system. The studies that explicitly aim to improve “railway safety” are divided into two categories. The first concerns the analysis and prevention of railway accidents based on investigation reports and after the system is put into service (feedback). The second category also aims at the analysis and prevention of railway accidents but rather based on manufacturer files as well as the experience and know-how of safety experts. This involves considering the analysis of accident risks from the design phase of the system and well before it is put into operation. This is why a distinction has been made between “accident prevention” in this second case and the analysis and understanding of the causes of accidents in the case of feedback.
- Harmonization of standards: 6% of the documents concern the harmonization of ISO standards and are based on the use of ontologies. An application that is also based on the ontology concerning the autonomous train.

**TABLE 4** Study results and positioning in relation to railway regulations.

Railway system	Subsystems	Equipment	Objectives	Authors	List of 65 articles
Structural elements	Rolling stock	Axle, wheels, ballast, rails, switch system, track geometry, locomotive, wagons	– Diagnosis, fault detection and failure prediction; – Inspection and maintenance of rolling stock.	[6, 7, 27–29, 31–38, 98]	14
	Infrastructure	Level crossings (LC) infrastructure	– Analysis of hazards related to railway accidents at the PN; – Infrastructure topology ontology.	[20, 76]	2
	Energy	Pantograph	Identifying the hazards associated with faulty pantographs	[30]	1
Functional elements	Telematics applications (TA)	TA_ Travelers TA_ Goods/Freight	– Ontology for customizing user interfaces; – Ontology for evaluating key performance indicators; – Ontology for searching personalized routes.	[39, 40, 77]	3
	Traffic operation and management	Locomotive, wagons, Metro, ERTMS/ETCS, Train driving	– Analysis and assessment of operational risks; – Driving assistance (train driver); – Rail traffic control; – Ontology for modelling ERTMS/ETCS; – Harmonisation of rail freight transport information systems.	[41–48]	9
Structural and functional elements	Maintenance	Rolling stock, Wagons, Metro	Rolling stock maintenance	[38, 49–55]	8
	Safety in tunnels	Railway tunnels	Construction of railway tunnels	[4]	1
	Infrastructure and rolling stock		Ontology and knowledge graph for “Route Compatibility” Search	[56–60]	5
	Autonomous train		ATMO ontology of autonomous train card	[84]	1
Railway safety	Analysis of railway accidents	From investigation reports	Analysis and prevention of railway accidents based on investigation reports (feedback)	[5, 49, 61–64, 66, 67]	8
	Analysis of railway accidents	From the manufacturers files	Analysis and prevention of railway accidents based on manufacturer files (from the system design phase)	[68–71]	4
		From railway standards	Ontology for the analysis of malfunctions in the design of railway systems.	[78]	1
Harmonization of standards			Ontology for the harmonization of ISO standards	[87–90]	4

The first findings that emerge from this literature review show:

- France is not yet aligned with other countries that are much more dynamic and responsive in the research and implementation of AI approaches and techniques in the field of rail transport, such as China, India, the United Kingdom and the United States.

- There are few (if not non-existent) studies that focus on the design, construction and consideration of safety from the specification and design phases of the rail system. The studies examined are mainly focused on the operation, maintenance and feedback phases.
- To our knowledge, there is no work that would consider the requirements imposed by Directive (EU) 2016/798 relating to railway safety in particular national reference value

(NRV), common security objectives (CSO), common safety indicators (CSI), safety certificate, safety approval, safety management system (SMS), change management (Modifications).

- The data, information and knowledge on safety come largely from accident and incident investigation documents and reports, ISO standards, infrastructure and rolling stock registers, specifications related to the European rail traffic management system: ERTMS/ETCS.
- The use of approaches based on ontologies and knowledge graphs seems interesting in the context of rail transport safety in order to improve at least the semantics, interoperability and reusability of knowledge in the field of safety.
- Deep learning approaches, including artificial neural networks (ANN), occupy an important place in applications dedicated to rail transport. However, despite their interests in terms of efficiency since they are based on digital learning as opposed to symbolic learning, they remain to this day qualified as black boxes. Authorities and railway safety specialists are still reluctant to apply these models in critical railway safety tasks. It is therefore appropriate to use new explainable artificial intelligence (XAI) approaches as a solution to improve these opaque models qualified as black boxes. However, during this literature review, only one application that integrates the explainability problem into AI using SHapley Additive exPlanations (SHAP) which is a unified framework for the interpretation of machine learning models. This new branch of AI, whose goal is to understand black box models and make the behaviour of these systems understandable and controllable by humans, has been addressed by several researchers: [22, 99–101].

## 9 | CONTRIBUTIONS AND LIMITATIONS OF THE STUDIED AI APPROACHES

Current AI approaches face two major obstacles. The first concerns the quality and availability of the data involved in a rail transport system and the second relates to the processing and interpretation of the data produced by machine learning algorithms. In addition, with complex models referred to as “black boxes,” it is difficult to understand how and why the internal reasoning mechanisms of the AI system impact the solution and predictions. The new explainable AI (XAI) approach may possibly provide an element of response to this problem. However, there is currently no real application to address a key problem such as rail safety.

The following two paragraphs give a quick overview of these two issues related to “data” and “explainability.”

### 9.1 | AI data issues involved in rail transportation

The study of all AI applications shows that the stages of acquisition, recovery, analysis, structuring, formalization, and

modelling, processing by learning and interpretation of the data produced pose a problem crucial in the field of rail transport. These data-related issues were also raised by [15] as part of his work on Big Data challenges specific to railway applications:

- The heterogeneity of the data collected, particularly during track monitoring, such as data on defects and rail geometry;
- The data used from different databases may be incomplete, inconsistent and sometimes subjective;
- Merging different databases such as ballast state data and runway geometric data still poses obstacles;
- Collection of real-time track data for maintenance purposes may have a time limit (deadlines);
- Data confidentiality.

Despite the interest in new approaches to improve the explainability of learning algorithms, “their use is not yet common and machine learning still does not have the rigor of traditional statistical methods” [102]. To this end, the authors detailed all of the “biases” involved in machine learning: Bias in data entry, Bias in data conservation (editing, transformation, labelling and enrichment) and Bias in data analysis especially when choosing learning algorithms.

To mitigate the subjectivity of data and therefore identify issues of “explainability” and “bias” in learning models, [103] suggested implementing two additional steps in the systems design process current learning processes: (1) understanding the subjectivity of the data involved in designing a learning system and (2) examining the social context in which the learning model is to be implemented. Furthermore, according to the author, it is not enough to focus only on the technology related to machine learning, but also to conceive of the socio-technical system in a broader way within which the learning model must be deployed.

Data-driven machine learning approaches are also critiqued in [104] by comprehensively reviewing several articles based on learning data from four aspects: paradigm, model, data source and the objective of learning. According to the author, machine learning systems implement five correlated tasks: collection, storage, processing, exploration and transformation of data. Thus, data is omnipresent throughout the development cycle of a learning system and the quality of knowledge and the models produced strongly depend on this data. Current learning techniques cannot, to date, replace the advantages of traditional approaches for several reasons [104] and in particular:

- The authors focus on the performance of learning models without realizing the distinction between domain knowledge and the processed data;
- Data preprocessing crucially influences machine learning results;
- Machine learning requires more prior knowledge of the application domain;
- Failure to consider the design of data structures can lead to results that suffer from “interpretability,” “generalization” and external “validity” and this problem of explainability and interpretability of results from learning systems poses a serious problem for users.

According to the authors, the main challenges and future directions of machine learning research concern not only the systematic consideration and integration of domain knowledge into the learning model, but also the development of new approaches to define explicitly the knowledge in order to improve the interpretability and generalizability of the results.

The problem related to training data was also highlighted and discussed in [105]. According to the authors, data availability, scarcity of labelled data, and confidence in the ability of learning models represent significant barriers to the development and adoption of machine learning methods. Indeed, the availability and accessibility of datasets to the public, the scarcity of labelled data which remains a laborious and costly task, often requiring specialized human expertise. As for data quality, which does not adequately represent the complexity of the real world, it frequently suffers from inconsistencies, noisy data, outliers and lack of standardized vocabulary. Therefore, reliance on the ability of models to learn from experimental and simulated data often fails to perform well in real-world settings. Furthermore, unlike some learning models like decision trees and linear models, which can contribute to interpretability and transparency in their decision-making processes, so-called “black box” deep learning models like neural networks, despite their performance, make the task of interpretability and explainability difficult for the end user. Therefore, it is paramount that research efforts should focus on explainable AI techniques [105].

To improve the reliability and security of complex systems [106], proposed a review of the state of the art (between 2016 and 2022) of physics-based machine learning methods whose objective the main objective is to exploit the wealth of traditional modelling approaches as “prior” knowledge in order to improve the effectiveness of machine learning models and in particular to address the problem of representativeness and completeness of learning data. Two types of physics-based machine learning approaches have been distinguished. The first relies on considering known physical constraints (loss functions) in learning models, which can be observed as a physics-based loss function. The second approach, called physics-based architecture, integrates physics knowledge into the structure of the learning model by the authors. According to the authors, future directions for the development of physics-based learning models require five major challenges: model selection, model structure, model parameters, model optimizer, and model prediction.

## 9.2 | Explainable artificial intelligence (XAI) as a solution to improve “black box” models

In AI and particularly machine learning, the terms *interpretability* and *explainability* are commonly interchangeable [107]. To understand how the AI model generates predictions, it is necessary to examine the internal reasoning mechanisms of the AI system in order to interpret the different particularities of the model allowing it to produce a given result. In this case, and in order to make the model transparent, we speak of interpretability. With complex models (or black boxes), it is difficult to understand

how and why the internal reasoning mechanisms of the AI system impact the solution and predictions. However, using an independent model like SHapley Additive exPlanations (SHAP), we can understand the meaning between the model input and output data, which helps explain the nature and behaviour of the AI model. So, explainability is the way of forcing an AI model to explain its behaviour in human terms. The concern to understand black box models and the desire to make the behaviour of these systems understandable and controllable by humans in particular AI systems based on multilayer neural networks whose predictions involve human lives motivated [99] to present a social conceptual framework for AI systems whose objective is to guide future research on explainable AI (XAI).

After a detailed and relevant study of AI applications in the railway field, [22] addressed the new explainable AI (XAI) approach, the objective of which is to make learning approaches and algorithms automatic, often “opaque” and described as “black boxes,” accessible to users. This new discipline of AI which, according to the authors has not yet received attention in rail transport, is based on three concepts [22]: *interpretability*, also called transparency, is defined by “the characteristic of a model of being at a level that makes sense for a human observer, thus allowing interventions aimed at making impartial decisions and improve robustness;” *Explainability* is the characteristic of a model taking actions and procedures to clarify its behaviour; *Understandability* is the characteristic of a model to represent its acquired knowledge in a way that humans can understand.

Understanding black box models has become essential as systems based on opaque artificial intelligence (AI) continue to thrive in various real-world applications. To master the complexities and nuances of explainable AI, [108] proposed a roadmap for future research which is based on 28 open problems classified into nine categories. This article highlighted advances in explainable AI (XAI) and described the challenges facing researchers in this field including developing explanations for new types of AI, improving current XAI methods, the clarification of the use of the concepts involved in XAI, the evaluation and adjustment of the methods and explanations proposed, favouring human-centred AI approaches, etc. Ref. [100] studied explainability and interpretability in a risk management context by identifying several considerations and characteristics of questions and concerns that could guide the development of risk analyst-related AI approaches:

- Key indicators for explainability and interpretability linked to the dimension of the risk study process;
- Key indicators for explainability and interpretability linked to the uncertainty management dimension;
- Key indicators for explainability and interpretability linked to the dimension of use and transfer of knowledge.

These indicators were applied to an example of an autonomous vehicle encountering the trolley problem.

To our knowledge, and in the field of railway safety, there is currently no AI approach that explicitly considers the explainability problem. Only an application that integrates



the explainability problem in AI using SHAP during the construction of railway tunnels [4].

## 10 | CONCLUSION

This study examined several methods, techniques, algorithms and applications of AI in the field of rail transport. It proposes a framework for the classification of these AI applications based on European railway regulations, in particular the three European directives relating to the development (Directive 2012/34/EU [1]), interoperability (Directive 2016/797/EU [2]) and safety of the European railway system (Directive 2016/798/EU [3]). Indeed, to help AI researchers, railway companies, infrastructure managers and national safety authorities, this synthesis work proposes to classify AI applications according to the structural elements (infrastructure, energy, rolling stock, control-command and signalling) and functional elements (operation and traffic management, maintenance, telematics applications) of the European railway system.

Useful both to researchers involved in the field of machine learning and knowledge engineering and particularly ontology engineering as well as to AI researchers and experts in railway safety, this work can serve as a resource and contributes to the present and future development of AI applications in the field of railway safety. However, certain remarks seem necessary.

In recent years and in the field of rail transport, researchers and experts in the field have become increasingly interested in the application of AI techniques and in particular machine learning to solve certain decision support problems, such as transport equipment diagnosis, maintenance operations management, driver behaviour analysis, prediction of transport infrastructure deterioration, planning and forecasting of traffic demand, traffic light control, etc. These methods are also used to extract the presence of informative entities on recurring accidents and incidents with a view to understanding the causes of accidents and finding causal relationships from accident investigation reports.

AI efforts to solve object *clustering*, *discrimination* (or classification), *regression* and *generalization* problems have resulted in a wide variety of learning methods, techniques, algorithms and systems applied to the field of computer security rail transport. However, this abundant literature makes it difficult to perceive the field, given the ambiguity of its vocabulary and the absence of rigorous reference definitions. To clarify certain essential concepts in the management of railway safety, we have used the regulations in force, in particular the three European directives relating to development (Directive 2012/34/EU [1]), interoperability (Directive (EU) 2016/797 [2]) and safety (Directive (EU) 2016/798 [3]) of the European rail system. These guidelines have been used to clarify not only structural and functional elements, equipment and components, but also to better formulate railway safety terms, concepts and requirements. The aim is to position the contribution of AI techniques in relation to current European legislation and regulations and therefore promote understanding and interest in new AI approaches by national safety authorities and railway operators.

However, despite the certain interest of the works analysed, each of the approaches developed concerns a particular application and does not cover all of the concepts involved in the field of rail transport and there are few works that focus on taking rail safety into account from the specification and design phases of the rail system. The work examined focuses mainly on the operation, maintenance and feedback phases. Data, information and knowledge on safety come largely from accident and incident investigation documents and reports, ISO standards, infrastructure and rolling stock registers, specifications linked to the European traffic management system, railway: ERTMS/ETCS and user information in terms of needs. Another important limitation concerns the terminology and concepts used to develop, for example, an ontology linked to railway safety. Certain works, such as those linked to ISO standards, ERTMS/ETCS and European registers, take into consideration the imposed terminology. In other works, based on “classic” AI, the vocabulary used suffers from a lack of precision and clarity, in particular the visible confusion between the term’s danger, risk, accident, incident, potential accident, dangerous event, dangerous situation, dangerous element, risk analysis, hazard analysis, risk assessment, risk management, risk reduction, security, safety etc. In this context, the vocabulary used when developing an AI system in particular to define classes, descriptors, properties, etc. cannot in any way guarantee the semantics, interoperability and reusability of knowledge. Consequently, the problem of the validity of certain approaches arises since these are approaches intended for risk management for critical systems such as rail transport. It should also be noted the absence (for certain applications) of common, identifiable and reusable concepts. This constitutes an obstacle for future work and the implementation of a common conceptual model which considers the semantics of all the terms and concepts used in railway safety and risk management is essential.

## 11 | PERSPECTIVES

Furthermore, the analysis of the field of railway safety has shown that the process of transferring knowledge from experts to the machine is complex and little studied and that the famous bottleneck in the development of a rail safety assistance system the decision is not limited to the sole phase of collecting data and learning examples but is also linked to the characteristics and formalization of this data and knowledge. On the one hand, the know-how of railway safety experts is based on empirical and sometimes subjective and implicit knowledge which can generate several interpretations, and on the other hand, there is generally no scientific explanation to justify this expertise compiled. This knowledge is not always conscious in the expert in the security field, understandable by a novice or sometimes even expressible through language. The transcription of natural verbal language into formal machine-interpretable language often causes a distortion of expert knowledge. This introduces a bias between the cognitive model of the expert and the model implemented on a machine learning system. This discrepancy is due not only to the fact that the representation languages used in

AI are not yet sufficiently rich to explain the cognitive functioning of the expert but also to the often-subjective interpretation of AI users and researchers. All these constraints restrict the field of investigation of the process of acquisition, transfer and processing of this knowledge. However, the introduction of machine learning systems working on examples makes it possible to generate new knowledge likely to help the expert solve a particular problem. Expertise in a field is not only held by experts but also distributed and stored implicitly in a mass of historical data that the human mind has difficulty synthesizing. Extracting relevant knowledge from this mass of information for explanatory or decision-making purposes constitutes one of the objectives of machine learning. However, learning from examples is insufficient to acquire all of the know-how of experts and requires recourse to the acquisition of other types of complementary knowledge. In this sense, each of the two approaches (acquisition and learning) can fill the weaknesses of the other. To improve the expertise transfer process, it is therefore interesting to reconcile these two approaches in the iterative process of knowledge acquisition. From initial knowledge of the domain (expert knowledge and historical data), the acquisition of knowledge makes it possible in particular to construct a model of the expert's reasoning and a model of representation of examples and to obtain a set of examples and object classes. This acquired knowledge is used by machine learning to produce new knowledge learned by the system which must then be evaluated by the domain expert. The comparison of the knowledge discovered through learning with the knowledge acquired from the expert makes it possible to enrich the initial knowledge of the field. There is always a gap between the knowledge acquired and the knowledge actually held by the expert.

Remember that in supervised learning, it involves learning to classify a new object (individual) among a set of predefined classes: we know the classes a priori. This involves learning a prediction function from annotated (or labelled) examples. On the contrary, in unsupervised learning, the number and definition of classes are not given a priori and it involves extracting classes or groups of individuals presenting common characteristics from unlabelled data. The semi-supervised learning approach lies between supervised learning which only uses known labelled data and unsupervised learning which only uses unlabelled data. This learning technique uses both a labelled and unlabelled dataset. The use of unlabelled data, in combination with labelled data, allows in our opinion to improve the quality of learning and particularly the problem of interpretability and explainability which to date constitutes the "bottleneck" learning techniques applied in high-risk systems such as rail transport security. Indeed, we can rarely extract all the data and knowledge from experts in the field on the first try, but when we present the knowledge learned by the system to the expert, he is aware of their interest, identifies contradictions, "holes" or relevant rules. It can provide advice on the choice of examples and descriptors, interpret the results produced by learning, improve the previously acquired expertise model, correct and complete the description language of the examples and adjust the learning parameters. By encouraging the expert to better verbalize his expertise, we therefore not only contribute to the enrich-

ment of knowledge in the field, but we also contribute to the interpretability of the learning models developed which today constitutes the main objective of the explanatory AI.

The obstacles linked to the formalization and capitalization of shareable and reusable knowledge bases have led research towards the development of new approaches based on ontology and knowledge graphs in order to better structure and formally represent knowledge and facilitate its reusability.

Another important point concerns the phase of identification and specification of the area of expertise which has often been neglected within the framework of this literature study. However, this crucial step in the knowledge acquisition methodology makes it possible to verify that the context of the problem is favourable for collecting knowledge, to verify the existence and availability of one or more experts in the field, to verify the presence of expertise in line with the objectives of the study and the possibility of attending real case treatments on the site for example. The domain identification step also makes it possible to understand the nature and origin of the information used by the expert as well as the specification of the form of solution to be developed by the planned decision support system. Several knowledge gathering techniques such as interviews or questionnaires can be used to identify the area of expertise. The benefit of this phase of acquisition and collection of data and knowledge makes it possible, among other things, to extract knowledge that is often implicit among experts and to make it more explicit and usable in two forms: surface knowledge and deep knowledge. After having clearly defined the field of study, the step of extracting surface knowledge consists of identifying the broad outlines of the expert's activity in the face of real problems. It aims to generally identify the mechanisms and modes of reasoning of the expert, the strategies and heuristics for solving the problem, the relationships between the key concepts of the domain, etc. The technique of verbalization and/or protocol analysis can be implemented during this stage in order to observe the expert at work. For the extraction of deep knowledge, this involves the detailed specification of the different knowledge modules as well as the refinement of the concepts used and their relationships. This step makes it possible, in fact, to precisely identify the expert's reasoning mechanisms. To carry out this step, the use of several knowledge collection techniques is necessary. The protocol analysis technique can be applied to acquire the observable part of the expert's activity. On the other hand, the conceptual sorting technique can be used to identify the mental organization of the concepts manipulated by the expert. This extraction step ultimately leads to the identification of the main facets of the expert's reasoning. The results of this step include detailed descriptions of all knowledge (object, class, entity) as well as problem-solving heuristics.

Several constraints can be raised during this phase of knowledge acquisition in close collaboration with experts in the field, such as the completeness of data, functions, concepts, relationships, classes of objects, etc., clarity, precision, unambiguity and consistency to remove any contradictions between data and knowledge.

It is also essential to have *evaluation knowledge* intended to assess the results produced by the learning system. This

evaluation, often neglected in the approaches studied, can be carried out by using, for example, a batch of *test examples* proposed by the expert in the field. The domain expert can also help evaluate and validate the knowledge learned. This approach involves intense interactivity and cooperation between the expert and the learning system which is not without consequences on the design of the interfaces. Other knowledge for processing *noisy data* is also necessary. If a learning algorithm makes it possible to generate rules or concepts from experimental examples, the fact remains that the quality of the knowledge learned depends largely on the quality of the example base (correct information, complete, consistent, rich, sufficient number of examples and descriptors). Machine learning is particularly sensitive to the relevance of the available data. Control of this quality is based in particular on the acquisition and use of additional knowledge to reduce diffuse noise in the examples. The production of usable knowledge leads to respecting various constraints:

- Ensure interactivity between the domain expert and the learning system: The system must explain its reasoning by producing knowledge understandable by the user or the domain expert whose role is to control, complete and validate this knowledge. This transparency of the approach requires particular care in the creation of human/machine interfaces,
- Guarantee the representativeness and completeness of the base of learning examples,
- Ensure resistance to “noise” to overcome the disturbing effects of poorly characterized examples,
- Consider the incrementality and scalability of knowledge to facilitate updating of knowledge.

The ability to acquire “good” knowledge despite the introduction of erroneous data (tainted by noise) and the incremental nature of the enrichment of the knowledge base are two important constraints for a learning system to be truly usable in an industrial environment. The notion of incrementality does not simply mean that the system accepts training examples one after the other. It is also necessary that when adding a new example, the modifications to be made to the learning system do not result in the complete reconstruction of the knowledge obtained from the examples already used. This characteristic of learning is often necessary to allow the use of the learned information when the training set is not yet sufficiently representative of the problem considered.

If the representation of knowledge, in the form of numerical and statistical data, commonly used by classic data analysis techniques, has proven to be very useful for the processing of simple observations, it is not suited to the processing of more complex knowledge complex. The numerical approach focuses on optimizing a global criterion such as entropy or a distance between examples in data analysis. The major disadvantage of numerical methods is not only the impoverishment of the initial data during their translation into number but also lies in the fact that the semantics of the numerical operations sometimes differ from that of the initial symbolic data. Furthermore, the knowledge generated is often incomprehen-

sible to humans. The numerical approach is efficient and has methods to resist the noise induced by erroneous data. On the other hand, the purpose of symbolic methods is to use knowledge in order to produce new knowledge which is not trivially presented in the initial description of the problem. This new knowledge constitutes an explanation at a higher level than that of observation in traditional data analysis. In the symbolic approach we no longer ask ourselves what is most effective but what is most meaningful. However, the major drawback of the symbolic approach is its sensitivity to noise which makes its application difficult when the learning population is highly incoherent. Combining these two approaches which pursue a common objective, the discovery of useful knowledge from facts, to inhibit their respective weak points, can certainly help to improve the learning process. Indeed, the simultaneous presence of quantitative and symbolic data and the imperfect nature of certain information make purely symbolic approaches insufficient. The symbolic operation of generalization of observations is a very complex and highly combinatorial process (several generalizations possible) which requires significant calculation time. This shows the interest of using numerical data relating to the examples to be generalized to accelerate the convergence of the generalization process. The symbolic approach is capable of explanations because it operates on data in the form of conceptual graphs, semantic networks, ontologies, etc. The use of a digital component is fundamental or even essential to optimize the learning process and deal with complex real problems where knowledge of the domain is often incomplete, non-exhaustive or noisy. These remarks attest to the interest of the *symbolic-numerical approach* for the creation of effective learning systems integrating the explanation component. The use of symbolic reasoning to promote explainability and interactivity with human experts constitutes an interesting contribution to the field of railway safety analysis. The numerical approach, for its part, is the essential complement to symbolic approaches to enable them to deal with real problems whose data are often noisy.

## AUTHOR CONTRIBUTIONS

Habib Hadj-Mabrouk proposes a literature review on the applications of artificial intelligence (AI) in particular machine learning (ML) in the field of rail transport safety. It proposes a classification of existing AI applications in accordance with European railway regulations and in particular Directive (EU) 2016/797 on the interoperability of the European railway system.

## CONFLICT OF INTEREST STATEMENT

The author declares no conflicts of interest.

## DATA AVAILABILITY STATEMENT

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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