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Review

A literature review of Artificial Intelligence applications in railway systems

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ABSTRACT

Nowadays it is widely accepted that Artificial Intelligence (AI) is significantly influencing a large number of domains, including railways. In this paper, we present a systematic literature review of the current state-of-the-art of AI in railway transport. In particular, we analysed and discussed papers from a holistic railway perspective, covering sub-domains such as maintenance and inspection, planning and management, safety and security, autonomous driving and control, revenue management, transport policy, and passenger mobility. This review makes an initial step towards shaping the role of AI in future railways and provides a summary of the current focuses of AI research connected to rail transport. We reviewed about 139 scientific papers covering the period from 2010 to December 2020. We found that the major research efforts have been put in AI for rail maintenance and inspection, while very limited or no research has been found on AI for rail transport policy and revenue management. The remaining sub-domains received mild to moderate attention. AI applications are promising and tend to act as a game-changer in tackling multiple railway challenges. However, at the moment, AI research in railways is still mostly at its early stages. Future research can be expected towards developing advanced combined AI applications (e.g. with optimization), using AI in decision making, dealing with uncertainty and tackling newly rising cybersecurity challenges.

1. Introduction

Artificial Intelligence (AI) is defined as a computerized system that is able to perform physical tasks and cognitive functions, solve various problems, or make decisions without explicit human instructions (Kaplan and Haenlein, 2019). Nowadays, AI has become one of the most important areas of research in almost all fields in academia and industry. Among many other sectors where mature applications of AI are flourishing, we notice that AI is still largely at its infancy stage in the railway sector. Nonetheless, emerging evidence has begun to show the potential of AI in railways and suggests that AI can play important roles such as optimizing

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complex railway systems, detecting infrastructure faults/defects, improving safety and security of urban rail networks and enhancing customer service quality (Burroughs, 2019). In addition, from a holistic point of view, Gibert et al. (2017) expect that AI will soon become a common tool used throughout the rail industry. The impact of AI on the railway sector is thus supposed to be pivotal, as there is evidence showing AI may completely revolutionize how certain railway areas operate, such as capacity management, life cycle cost, maintenance, passenger flow prediction, and significantly reduce errors from both humans and computers, high-level automation and auto-adaptive systems. Recent developments of the applications of AI to railway have already emerged. For instance, Toshiba has built an AI system that can enhance the train timetabling for Greater Anglia, a train operator in the UK (Fragnelli and Sanguineti, 2014). The French operator SNCF already uses an AI-based predictive maintenance on Transilien commuter trains in the Paris region (SNCF, 2020).

A primary definition associates AI to any machines acting in a way that seems intelligent (Przegalinska, 2019) or exhibiting characteristics that are typical of human reasoning. This definition suffers from the lack of a universally accepted definition of “intelligence”. Later a new definition was developed based on the famous Turing Test (Turing, 2009): a machine is deemed intelligent if it is indistinguishable from a human during an interaction with an impartial observer. Over the years, more structured and detailed definitions have been introduced, e.g. European Commission (2018), European Commission and Joint Research Centre (2019) and Copeland (2019). These definitions try to capture the broad nature of AI and its potential coverage. For certain domains, such definitions may be too abstract and thus are less likely to be widely accepted. Overall, such general definitions tend to reduce the uptake leading to no common agreement on what AI actually represents. To address this challenge, we have proposed the following definition of AI in Bešinović et al. (2021), which is suitable to support next-generation railway transport and traffic engineering: *AI is the discipline gathering all the aspects that allow an entity to determine how to perform a task and/or make a decision based on the experience matured by observing samples and/or by interacting with an environment, possibly competing against or cooperating with other entities*. This definition is based on the need to emphasize the following aspects that are crucial when considering AI application in the railway domain: (1) Being able to learn from examples (i.e. not coded to solve a task by a programmer), (2) Possibly operating in an environment populated by other entities, (3) Accomplishing a task that would require intelligence if done by a human, (4) Not include a trivial automatism, and (5) Can be both hardware or software (or a hybrid). What stated so far allow us to also highlight the relationship between some of the most spread AI-related concepts including, for example, Deep Learning (DL), Machine Learning (ML), and the AI itself. We would like to clarify that Machine Learning is a subarea within AI addressing the techniques that are able to learn from examples and improve with experience, without being explicitly programmed for a given task. Within ML, Artificial Neural Networks (ANNs) are inspired by the structure of human brain: an ANN has a layered structure composed of interconnected neurons (i.e., perceptrons), which interact with each other to perform a given task. In recent years, the technological evolution allowed engineers to build increasingly complex ANN, such as the so-called Deep Neural Networks (DNN), which are a class of ANNs with several layers of neurons, allowing them to automatically extract features from data. DNN enable Deep Learning, which “allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction” (LeCun et al., 2015).

In Bešinović et al. (2021), we have proposed a systematic taxonomy of AI based on the above definition where we divide various branches and study areas of AI into several General AI Fields including (i) Expert systems; (ii) Data Mining; (iii) Pattern Recognition; (iv) Adversarial Search; (v) Evolutionary Computing; (vi) Machine Learning; (vii) Operations Research and Scheduling; (viii) Logic Programming; (ix) Natural Language Processing & Speech Recognition; (x) Computer Vision & Image Processing; (xi) Autonomous Systems & Robotics. These general AI fields will be used throughout this paper. The readers can refer to Bešinović et al. (2021) and RAILS D1.1 (2020) for more details in the definition and taxonomy of AI in the railway context.

There are a number of review papers in the literature dedicated to the application of AI in railways. However, all of these surveys tend to focus on a specific aspect of the combination of AI and railway sub-domains. For instance, in Ghofrani et al. (2018), a review of the recent applications of big data analytics in the context of railway engineering and transportation was conducted. A survey of the existing and potential use of AI in railway assets was provided in Jain and Yogesh (2019). In Wen et al. (2019), a review and appraisal of data-driven approaches applied in train dispatching management was given, where data-driven approaches are grouped into statistical methods, graphical models and ML. Chenariyan Nakhaee et al. (2019) gave a survey on recent applications of ML in rail track maintenance. The authors provided a taxonomy in classifying the existing literature. In addition, they presented the shortcomings of current techniques and discussed certain remedies for the research community and rail industry. Liu et al. (2020) gave a review of applications of visual inspection technology based on image processing in the railway industry. In Xie et al. (2020), urban flow prediction from spatiotemporal data was systematically reviewed and existing urban flow prediction methods based on ML were overviewed with some discussions on the difficulties and some ideas in this direction. A review on railway system resilience was presented in Bešinović (2020) focusing on quantitative approaches. The review discussed resilience metrics and approaches, where the latter contains data-driven and optimization-based approaches. Several rising future scientific topics were identified as well. Corman and Meng (2015) presented a survey of the recent approaches on online railway traffic rescheduling problems, including both dynamic and stochastic aspects; the authors concluded by stating that optimization-based models were the most used approaches. So far, the literature in this field of AI and railways lacks a holistic overview, which desirably would, on one side, take a broad perspective of AI, and on the other side, consider railway system as a whole, i.e. cross-map with various sub-domains of the railway sector. According to what we have investigated in the peer’s review work as well as the expected outcomes we want to achieve in this study, we summarized the review papers we mentioned before and made a comparison among them in Table 1.

To understand the current position of AI as a whole in railways, this paper reviews the state-of-the-art research studies to recognize the current worldwide focuses and results with the aim of determining a variety of targeted AI applications for railway systems and analysing their patterns and distributions. Given the vastness of the rail sector, we holistically subdivided it into seven

Table 1
A comparison table concerning the applications of AI fields, including other related review papers and this study. Not defined: there is no evidence found that a corresponding analysis/scope definition conducted. Partially defined: there may be a brief discussion about relevant analysis but no explicit supportive figures/tables. Well defined: Besides the conducted analysis, straightforward tables/illustrations have been provided to explain the analytic statement.

Paper	AI Field	Railway sub-domain	Time range/ Review size definition	Distribution analysis	Trend analysis	Matching between AI techniques and rail sub-domains
Ghofrani et al. (2018)	Big data analytics	Asset maintenance Traffic flow prediction Traffic accidents analysis Travel route planning Transport service planning	Not defined	Not defined	Partially defined	Partially defined
Jain and Yogesh (2019)	Big data Visual analytics	Track defect detection	Not defined	Not defined	Not defined	Not defined
Wen et al. (2019)	Data-driven analysis	Train dispatching management	153 papers	Well defined	Well defined	Well defined
Chenariyan Nakhaee et al. (2019)	Shallow learning-based ML Deep learning-based ML	Railway track maintenance	Not defined	Partially defined	Partially defined	Well defined
Liu et al. (2020)	Image processing Visual inspection Computer vision	Track defect detection Pantograph–Catenary system maintenance Train body defect detection Infrastructure defect detection	123 papers	Not defined	Partially defined	Not defined
Xie et al. (2020)	Traditional machine learning-based Deep learning-based methods Reinforcement learning-based Transfer learning-based	Crowd flow prediction Traffic flow prediction Public transit flow prediction Trajectories data analysis	2014–2019	Not defined	Partially defined	Well defined
Bešinović (2020)	One of the surveyed method is data-driven	Resilience of Railway System	2008.01-2019.08 59 papers	Well defined	Well defined	Well defined
Corman and Meng (2015)	Online dynamic methods (Open-loop approaches Close-loop approaches)	Online railway traffic rescheduling	Not defined	Partially defined	Well defined	Not defined
Our paper	All fields introduced in Section 1	Maintenance and inspection Safety and security Autonomous driving and control Traffic planning and management Passenger mobility Revenue management Transport policy	2010–2020 139 papers	Well defined	Well defined	Well defined

sub-domains in order to carry out a more structured review and describe different complementary aspects of railway system. Then, we separately analysed the literature related to the different sub-domains to identify promising future research directions to facilitate further uptake of AI by academia and industry. The seven sub-domains (that we have widely discussed in RAILS D1.1 (2020)) are introduced as follows.

Maintenance and Inspection covers all preventive and corrective activities intended to keep a system or sub-system in proper operating condition. These activities are essential to avoid deterioration with possible consequences on safety because of improper maintenance.

Safety and Security are concepts of primary concern for any transport system, as travellers expect transportation to be safe and secure. Transport Safety and Security refers to all activities and means reducing the risks of both unintentional and intentional causes of accidents that may directly or indirectly cause injury to persons and/or damage to physical assets.

Autonomous Driving and Control involves applications oriented at making trains capable of operating automatically without any (or with only limited) human intervention and approaches oriented at optimizing energy consumption of running rolling stock. The International Association of Public Transport (UITP) defines five Grades of Automation (GoA) with respect to train operation ranging from GoA0, which means no automation, to GoA4, which expects trains capable of operating automatically without on-board staff/driver. See Yin et al. (2017) for an in-depth review on the research and development of automatic train operation in railway.

Traffic Planning and Management includes all the activities that deal with effective and efficient capacity management, timetabling, control of railway operations as well as resource allocation and resource management. This includes traffic state

Table 2
Keywords pairs used in the first step.

Rail sub-domains	Maintenance and Inspection; Safety and Security; Autonomous Driving and Control; Traffic Planning and Management; Revenue Management; Transport Policy; Passenger Mobility
General AI field	Expert systems; Data Mining (DM); Pattern Recognition; Adversarial Search; Evolutionary Computing; Machine Learning; Operations Research and Scheduling; Logic Programming; Natural Language Processing (NLP) & Speech Recognition; Computer Vision (CV) & Image Processing (IP); Autonomous Systems & Robotics

prediction and traffic rescheduling, analysis of passenger and freight railway transport, estimation of traffic demand and capacity, scheduling of trains and crews, optimal use of rolling stock and energy in order to increase the efficiency and competitiveness of passengers and freight transport.

Revenue Management is the application of disciplined analytics that predict consumer behaviour at the micro-market levels and optimize product availability and price to maximize revenue growth.

Transport Policy deals with the development of a set of strategies and programmes, that are established by governments and regulatory bodies to achieve specific objectives relating to social, economic and environmental conditions, and the functioning and performance of the transport system.

Passenger Mobility refers to the movement of people using any kind of transport means. In this context we refer to railway transportation and to the following mobility characteristics: *Time*, that is the time needed to reach the destination; *Affordability and Accessibility*, as the rail options need to be affordable and accessible to provide a successful transport service; and *Safety*, that is the essential precondition for rail mobility.
This paper is expected to be useful to:

- Junior academics to draw attention towards open challenges in applying AI to railways and to get familiar with the state-of-the-art;
- Senior academics to provide a multidisciplinary research roadmap and generate new scientific ideas; and
- Practitioners to understand common terminologies, recognize diverse applications and future implementations in designing and assessing AI-based applications in railways.

This paper is organized as follows. Section 2 gives the methodology used for searching the selected papers in this work and provides an overview of the selected papers in several aspects such as journal distribution, year distribution, sub-domain distribution and targeted focuses. Section 3 surveys state-of-the-art papers over the defined seven railway sub-domains and provides insights based on the survey results. Section 4 presents future directions for the research on AI in the railway sector. Finally, Section 5 provides final remarks.

2. Review methodology and overview on papers

In this section, we describe how we carried out the procedure of mining and classifying the contributions from the reviewed papers. Then, distribution analysis regarding the papers resulting from this process will be provided from different perspectives.

2.1. Literature review methodology

To give a comprehensive overview on the state-of-the-art of AI-based applications in rail systems, we initially followed the methodology proposed by Kitchenham (2004). We used the Scopus[1] database as the main source, and Google Scholar[2] as a supplementary source, and also restricted the searching scope to academic papers in English, including journal papers and conference proceedings from January 2010 to December 2020. However, since Artificial Intelligence and Rail are two wide domains, creating an all-encompassing and well-structured search query was not straightforward. Specifically, to obtain the papers in this systematic literature review, we went through the following steps. First, we initially searched for macro-areas considering the terms listed in Table 2 in pairs, combining a railway subdomain (as mentioned in Section 1) and an AI field (as defined in Bešinović et al. (2021)), e.g. "Maintenance and Inspection" & "Machine Learning". This was done on the title, abstract and keywords. Second, we additionally included relevant (e.g. with a high number of citations) papers that were published before 2010, and some papers we previously analysed in RAILS D1.1 (2020) but were not covered by the first step. Third, we manually filtered and removed the non-relevant ones (i.e. those that did not rely on AI-based techniques). Fourth, we further explored the literature databases using the additional specific (subdivided) AI terms shown in Table 3 to ensure that diverse AI applications were covered. Finally, we performed a thorough manual investigation of the obtained papers based on full texts and carefully analysed them by evaluating their objectives, proposed methods, real contributions/solutions and future directions. We eventually obtained 141 papers to do the review work.

[1] https://www.scopus.com/home.uri.
[2] https://scholar.google.com/.

Table 3
AI sub-areas used in the fourth step.

General AI fields	Corresponding AI sub-areas or algorithms
Expert Systems	Rule-based Expert Systems; Fuzzy Expert Systems; Neuro-Fuzzy Expert Systems
Data Mining	Big Data Analytic
Pattern Recognition	Pattern Recognition
Adversarial Search	Deep Reinforcement Learning; Agent-based Modelling
Evolutionary Computing	Evolution Strategies; Genetic Programming; Genetic Algorithms (GAs); Multi-Objective Evolutionary Algorithms ; Swarm Intelligence
Machine learning	Deep Learning; Deep Neural Networks; Convolutional Neural Networks (CNNs); Supervised Learning; Unsupervised Learning
Operations Research and Scheduling	Linear Programming; Integer Programming; Nonlinear Programming; Dynamic Programming; Constraint Programming; Network Flows and Graph Theory; Scheduling
Logic Programming	Abductive Logic Programming; Meta Logic Programming; Constraints Logic Programming; Concurrent Logic Programming
Natural Language Processing & Speech Recognition	Knowledge Extraction; Word Segmentation; Lemmatization; Stemming; Sentiment Analysis
Computer Vision & Image Processing	Object Recognition; Optical Character Recognition; Movement Tracking; Image Acquisition; Feature Extraction; Image Understanding
Autonomous Systems & Robotics	Robot Behaviour Control; Active Sensory Processing and Control; Sensor Data Integration

Table 4
Numbers of papers in journals and conference proceedings.

Journal/Conference	Number of selected papers
Transportation Research Part C: Emerging Technologies	10
IEEE Transactions on Instrumentation and Measurement	5
Sensors	5
IEEE Transactions on Intelligent Transportation Systems	4
Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit	4
Expert Systems with Applications	4
IEEE Access	4
Engineering Applications of Artificial Intelligence	3
Journal of Advanced Transportation	3
arXiv	2
IFAC-PapersOnLine	2
Measurement	2
Journal of Transportation Engineering, Part A: Systems	2
Public Transport	2
Applied Sciences	2
IET Intelligent Transport Systems	2
IEEE International Conference on Big Data	2
Transportation research record	2
Other journals and proceedings	81
Total	141

2.2. Distribution of papers per journal or conference

Table 4 summarizes the reviewed papers by considering their publication sites (i.e., journals and conference proceedings). Due to the large numbers of papers and the journals/proceedings, we only present the journals/proceedings having more than one paper in our collection. Table 4 gives the distribution of investigated papers against different journals/proceedings. which is dominated by the transport-related journals, for example, *Transport Research Part C: Emerging Technologies*, *IEEE Transactions on Intelligent Transportation Systems*, *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, *Journal of Advanced Transportation* and *Journal of Transportation Engineering, Part A: Systems*. Papers discovering the potential of AI in railway sub-domains are more often published in journals that are more AI/engineering-focused, such as *Expert Systems with Applications*, *Engineering Applications of Artificial Intelligence* and *Sensors*. All in all, the selected papers are not evenly distributed across the investigated journals/conferences and several popular journals can be identified.

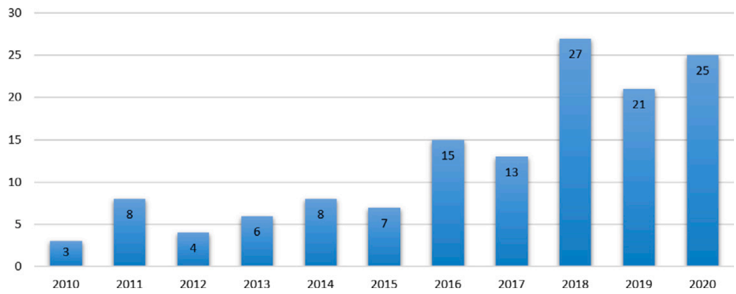

Fig. 1. Distribution of papers for the period 2010–2020.

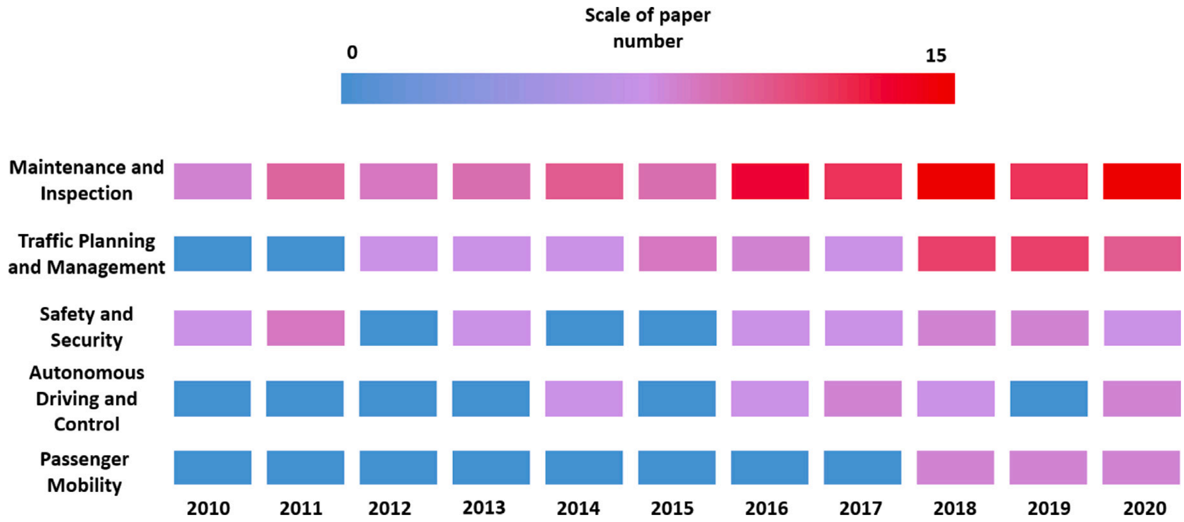

Fig. 2. Distribution of papers in each rail sub-domain over years.

2.3. Numbers of papers over years: aggregated and disaggregated

Now we systematically inspect the selected papers from a quantitative angle by measuring the details of how these studies distribute over the ten-year period. We summarize the numbers of papers over the years in Fig. 1. There are only 4 relevant papers found which were published before 2010 so that they are not displayed in this figure. The sum of available studies before the end of 2015 was noticeably lower. However, the number of qualified papers has been significantly increased since the year 2016, exceeding 20 in the years 2018, 2019, and 2020.

We further analyse the reviewed papers based on the railway sub-domains defined in Table 2 against the years of publication. Fig. 2 gives a heat map showing the numbers of papers in five popular railway sub-domains over the 10-year horizon. *Maintenance and Inspection* is the most popular research field compared to other sub-domains throughout the ten years. Despite of some fluctuations in the first five years, the number of papers in this field generally rose reaching 15 papers in 2018 and 2020. Following that, *Traffic Planning and Management* and *Safety and Security* also attracted many studies throughout. AI-related research mainly began to appear in *Autonomous Driving and Control* and *Passenger Mobility* in the second half of the ten years. No paper was found in *Revenue Management* and *Transport Policy* between 2010 and 2020.

2.4. Paper distribution in railway sub-domains

Fig. 3 and Table 5 present the information on the number of papers included in each sub-domain of railway. *Maintenance and Inspection* is the primary component which makes up around 57% of the studies: more than twice the amount of papers in *Traffic Planning and Management* and seven times the papers in *Safety and Security*. Papers in *Autonomous Driving and Control* and *Passenger Mobility* account for 5% each . Research paper on the sub-domain of *Revenue Management* and *Transport Policy* has not been discovered. Table 5 provides a list of reviewed papers classified per sub-domains.

In addition, we classify the papers based on the specific topics within each sub-domain and then generated five stacked bar charts to uncover the specific research problems/topics tackled (See Fig. 4). In *Maintenance and Inspection*, defect detection yields the most prominent research trend; up to 49% of the papers chose this topic. Researchers also have shown an interest in defect

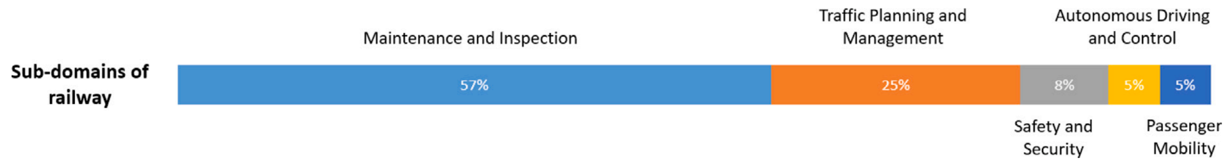

Fig. 3. Proportions of papers in rail sub-domains.

Table 5
Different rail sub-domains investigated among the selected papers.

Rail sub-domain (frequency)	References
Maintenance and inspection 81 papers (57%)	Eker et al. (2011), Guler (2013), Hu et al. (2019), Jamshidi et al. (2017b), Jayaswal et al. (2011), Khouzani et al. (2017), Li et al. (2011a), Pu and Wang (2014), Fumeo et al. (2015), Marsh et al. (2016), Ou et al. (2019), Rabatel et al. (2011), Sammouri et al. (2013), Sharma et al. (2018), Allah Bukhsh et al. (2019), Cherfi et al. (2012), de Bruin et al. (2017), Faghih-Roohi et al. (2016), Famurewa et al. (2017), Firlik and Tabaszewski (2020), Gao et al. (2018), Giben et al. (2015), Gibert et al. (2017), Fink et al. (2013), Guler (2016), Hajizadeh et al. (2016), Han et al. (2020), Hu and Liu (2016), Jamshidi et al. (2018), Jiang et al. (2019), Kang et al. (2019), Krummenacher et al. (2018), Lasisi and Attoh-Okine (2018), Lee et al. (2018), Li et al. (2014), Ritika and Rao (2018), Sadeghi and Askarinejad (2012), Santur et al. (2016a), Santur et al. (2017), Santur et al. (2018), Shang et al. (2018), Shebani and Iwnicki (2018), Soukup and Huber-Mörk (2014), Sysyn et al. (2019a), Sysyn et al. (2019b), Tsunashima (2019), Wang et al. (2018), Wei et al. (2019), Xia et al. (2010), Xu et al. (2018), Yin and Zhao (2016), Zhang et al. (2020b), Zhou et al. (2016), Liu et al. (2016), Sammouri et al. (2014), Ferrari et al. (2018), Lee et al. (2016), Feng et al. (2014), Gibert et al. (2015), Posada Moreno et al. (2020), Santur et al. (2016b), Trinh et al. (2012), Moura and Erden (2017), Schlake et al. (2010), Vithanage et al. (2017), Vithanage et al. (2018), Liu et al. (2016), Zhou et al. (2014), Jamshidi et al. (2017a), Yao et al. (2020), Wang et al. (2020c), Chen et al. (2020), Wang et al. (2020a), Geng et al. (2020), Carboni and Crivelli (2020), Na et al. (2020), Tu et al. (2020), Luo et al. (2020), Sikorska et al. (2011), McMahon et al. (2020) and Zarembski (2014)
Safety and security 12 papers (8%)	An et al. (2011), Ćirović and Pamučar (2013), Gul and Celik (2018), Li et al. (2011b), Alawad et al. (2020), Zhang et al. (2018), Hadj-Mabrouk (2019), Zilko et al. (2016), Sturari et al. (2017), Maire and Bigdeli (2010), Wohlfeil (2011) and Zaman et al. (2019)
Autonomous driving and control 7 papers (5%)	Nowakowski et al. (2018), Zhang (2017), Yin et al. (2014), Brenna et al. (2016), Carvajal Carreño (2017), Wang et al. (2020b) and Hua et al. (2020)
Traffic planning and management 34 papers (25%)	Deng et al. (2018), Fay (2000), Schaefer and Pferdmenges (1970), Zhuang et al. (2016), Liu et al. (2018), Cerreto et al. (2018), Wang and Zhang (2019), Kecman and Goverde (2015), Kecman and Goverde (2015), Schüpbach et al. (2018), Tormos et al. (2008), Barman et al. (2015), Ho et al. (2012), Pu et al. (2019), Wang et al. (2019b), Wang et al. (2019c), Zheng et al. (2014), Khadilkar (2019), Obara et al. (2018), Oneto et al. (2017), Ning et al. (2019), Peer et al. (2018), Roost et al. (2020), Salsingikar and Rangaraj (2020), Goverde et al. (2016), Yin et al. (2018), Xue et al. (2019), Bešinović et al. (2013), Prokhorchenko et al. (2019), Barbour et al. (2018), Kuppusamy et al. (2020), Hickish et al. (2020), Ying et al. (2020) and Huang et al. (2020)
Passenger mobility 7 papers (5%)	Xu et al. (2004), Gallo et al. (2019), Heydenrijk-Ottens et al. (2018), Liu et al. (2019), Zhu et al. (2018), Zhang et al. (2020a) and Velastin et al. (2020)

prediction and fault detection and diagnosis, with 12% and 16% of articles classified as these two topics respectively. In *Traffic Planning and Management* the percentage of papers that explore rescheduling problems more than tripled the figure for those solving railway capacity tasks. Delay analysis/prediction was also a popular research direction and the percentage of papers which paid attention to this holds the same level with rescheduling issues (23%). Secondly, 20% of the selected papers fall into the group of train timetabling, while the figure was higher than that of railway disruption, conflict prediction and other remaining topics. Risk management is the mainly discussed topic of *Safety and Security*, with 33% studies classified in and it more than four times of the proportion of critical software and anomaly detection (8%). While the remaining papers evenly distribute among the topics of railway accidents, railway disruption and collision avoidance with proportion of 17%. Energy optimization is the hottest topic among the sub-domain of *Autonomous Driving and Control*, more than half of the papers included in this group (57%). The remaining research directions — verification, intelligence train control and train trajectory, hold the same proportion, with around 14% of the studies involved in each of these topics respectively. Finally, within Passenger Mobility, authors focused mainly on passenger flow prediction.

3. Paper reviews by railway sub-domains

In this section, we present the reviewed papers by clustering them based on railway sub-domains covering Maintenance and Inspection, Safety and Security, Traffic Planning and Management and Passenger Mobility. Within each subdomain, we classified the papers according to the problem they addressed and, for each paper, we also highlighted the specific exploited AI techniques/applications and used data.

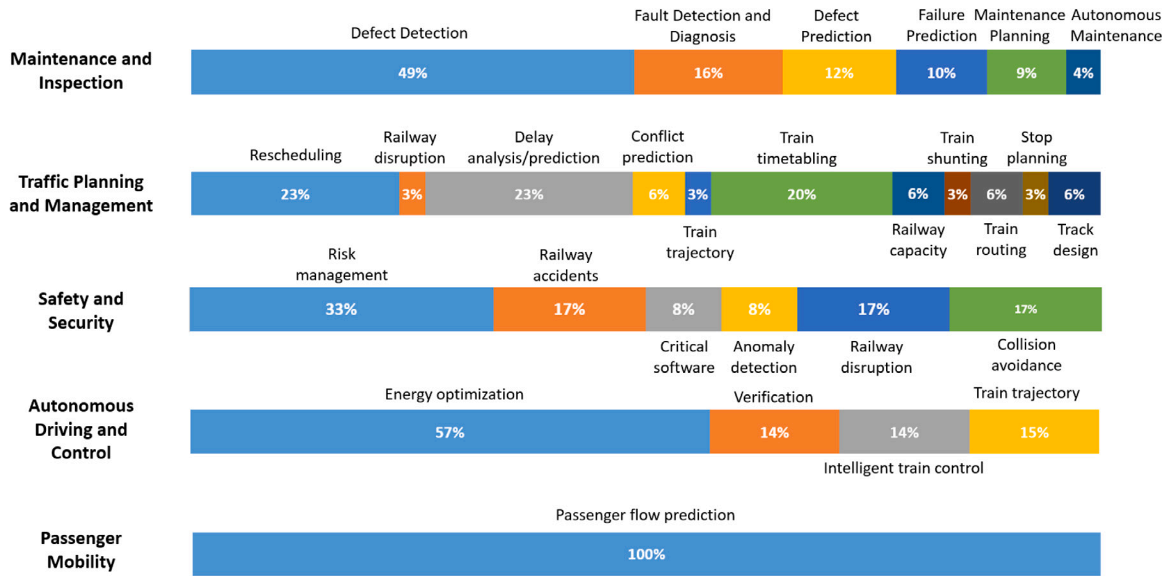

Fig. 4. Papers in 5 railway sub-domains with respect to their focus.

3.1. Maintenance and inspection

The Maintenance and Inspection subdomain includes activities aiming at assessing the deterioration and/or the operating status of complex mechanical and electrical systems that make up the railways. In this context, we found various applications of AI tackling diverse problems including: (i) *defect detection*, addressing the identification of physical defects such as cracks, missing items, and scratches within railway components; (ii) *fault detection*, which deals with the identification of faults or anomalies in electrical and similar components, and diagnosis, aiming to identify the faults causes; (iii) *defect prediction*, aiming at predicting the evolution of the defects such as track deterioration; (iv) *failure prediction*, concerned with forecasting the state of a component that deviates from its nominal behaviour; (v) *maintenance planning*, including decision support systems allowing dynamic scheduling of maintenance and inspection activities ; (iv) *autonomous maintenance*, aiming at obtaining intelligent and automated inspection activities.

Defect Detection. Most of the studies focused on railway tracks, rolling stocks, and catenaries. Beyond these three areas, Ferrari et al. (2018) dealt with the identification of defects within railway signalling requirements documents leveraging NLP applications.

Tracks. We identified three main track-related subareas: fastening system, track geometry/structure, and rails. Focusing on fastening systems inspection and defect detection, an Adaboost-based approach was implemented both in Trinh et al. (2012), to train multiple classifiers to identify defective anchors and Xia et al. (2010), to detect broken fasteners. In addition, also a Latent Dirichlet Allocation generative statistical model (Feng et al., 2014) and DNNs (Wang et al., 2018; Wei et al., 2019) were exploited to detect fasteners defects. We also recognized three correlated papers by the same authors proposing a model based on Support Vector Machines (SVMs) and Histograms of Oriented Gradients features to detect fastening types and defects (Gibert et al., 2015), a semantic segmentation approach based on Fully-Convolutional Neural Network to accurately localize and inspect the condition of railway components using greyscale images (Giben et al., 2015) and, finally, leveraging the results obtained in these studies, a new multitask learning framework to detect fasteners type and defects and to identify materials within images (Gibert et al., 2017).

Regarding track geometry, Neural Networks (NNs) (Sadeghi and Askarinejad, 2012), SVMs (Tsunashima, 2019), and Big Data (Zarembski, 2014) were exploited to detect defects. SVMs were also investigated together with Linear Discriminant Analysis (LDA) and Random Forest (RF) basing on Track Quality Indices obtained through a Principal Component Analysis (PCA) approach (Lasisi and Attoh-Okine, 2018). Also, the Faster R-CNN (Region-based CNN) architecture (Ren et al., 2015) was exploited to recognize tracks subgrade defects (Xu et al., 2018). According to Zarembski (2014), it is feasible that combining track geometry data with rail defect data and Vertical Track Interaction (VTI) data together to forecast the rate of track defect development and the correspond replacement requirements for rail.

The last subarea regards rails surface and structural defects. Regarding DL methods for rail surface defect detection, mainly CNN-based architectures have been implemented (Santur et al., 2017; Soukup and Huber-Mörk, 2014; Faghih-Roohi et al., 2016; Santur et al., 2018; Jamshidi et al., 2017a) and a transfer learning approach (Shang et al., 2018).

In addition, different traditional ML approaches were exploited for rail surface defect detection such as Linear SVM (Gao et al., 2018), RF (Santur et al., 2016a), unsupervised approaches in combination with PCA (Famurewa et al., 2017), and a semi-supervised approach with different sampling methods to cope with imbalanced data (Hajizadeh et al., 2016). Also, NNs were exploited to detect tracks' technical conditions (Firlik and Tabaszewski, 2020). Lastly, hybrid approaches exist combining multiple methods. Jiang et al. (2019) combined Wavelet Packet Transform to decompose the signal of surface defect in different frequency bands, Kernel Principal

Component Analysis (KPCA) to reduce the feature space, and SVM to classify rail contact fatigue defects; while (Santur et al., 2016b) investigated PCA, KPCA, Singular Value Decomposition, and Histogram Match to extract features from video data, and then, applied a RF model to detect rail surface defects.

Rolling Stock. Regarding rolling stock, the analysed studies mostly focused on bogies which include different components such as bolts, angle cocks, and wheels. As ML techniques, SVMs have been exploited to detect angle cock defects (Zhou et al., 2014), and fastening bolt defects in combination with gradient coded co-occurrence matrix (GCCM) features (Liu et al., 2016). The same combination was also exploited by Liu et al. (2016) using GCCM features to train, through an Adaboost approach, a cascade detector to identify bogie block key areas and then an SVM to classify defects. From a Deep Learning perspective, authors leveraged CNNs to detect wheel defects (Krummenacher et al., 2018) and investigated several Computer Vision approaches for underframe components inspection (Schlake et al., 2010). Additionally, Yao et al. (2020) exploited an improved YOLOv3 architecture to detect foreign bodies (e.g. plastic bags) under the train frame. Lastly, beyond the bogie component, Posada Moreno et al. (2020) paved the way for a future health estimation framework and decision support system for wagon maintenance implementing an RCNN-based wagon identifier, while Na et al. (2020) combined R-CNN and SVMs to detect pantograph contact strips wear defects.

Catenaries. Han et al. (2020) and Kang et al. (2019) relied on Faster R-CNN to detect defects of catenaries' components. Particularly, the latter also considered a deep multitask learning scenario and merged two networks, a deep material classifier and a Deep Denoising Autoencoder, to define the state of the defects. Additionally, Wang et al. (2020a) focused on catenary split pins defect-classification by combining two YOLOv3 and a DeepLabV3+ architectures, while Tu et al. (2020) presented a CNN named RobotNet to efficiently detect catenary components.

Fault Detection and Diagnosis. Papers under this category addressed issues related to tracks, rolling stock, and maintenance equipment. Focusing on traditional ML techniques, SVMs were the most involved in railway turnout fault diagnosis supported by a feature space reduction through PCA (Zhou et al., 2016), and both PCA and LDA (Ou et al., 2019). Further, SVM were also combined with mel-frequency cepstrum coefficients for Railway Point Machines defect detection and diagnosis through audio analysis (Lee et al., 2016). As other ML techniques: a semi-supervised approach, built on an extension of the Expectation–Maximization algorithm, was proposed to learn a statistical model based on Independent Factor Analysis for track circuit fault diagnosis (Cherfi et al., 2012); a model based on Quadratic Discriminant Analysis was built for turnout monitoring and fault detection (Sysyn et al., 2019b); and, lastly, back propagation Artificial Neural Networks (ANNs) were exploited for maintenance equipment diagnosis (Pu and Wang, 2014). In addition, two expert systems based on wavelet transform, ANN and fuzzy rules for rolling bearings fault diagnosis were presented (Jayaswal et al., 2011); another expert system was used for database establishment for onboard equipment real-time monitoring and diagnosis (Li et al., 2011a); and, roughly for the same purpose, a Data Mining approach involving a knowledge base built on historical data and a pattern recognition model was implemented to identify anomalies in data coming from train sensors (Rabatel et al., 2011). Concerning DL approaches: a Recurrent Neural Network (RNN) was implemented to measure the spatial and temporal dependencies of faults in track circuits (de Bruin et al., 2017); a Deep Belief Network was used for onboard equipment fault diagnosis (Yin and Zhao, 2016); a simplified shallow information fusion CNN was developed to cope with axle-box bearings fault diagnosis (Luo et al., 2020); lastly, both a capsule neural network (Chen et al., 2020) and a deep residual network (Geng et al., 2020) were exploited for train bogie fault diagnosis. Notably, the approach proposed by Geng et al. (2020) was thought to cope with unbalanced data.

Defect Prediction. Under Defect Prediction, researchers mainly focused on track-related elements and analysed track geometry, track deterioration, and rails defects. In addition, some studies incorporated rolling stocks aspects as well. Beyond these areas, Ritika and Rao (2018) leveraged Inception-v3 network (Szegedy et al., 2016) to predict vegetation overgrowth and rail, while Carboni and Crivelli (2020) investigated the possibility to exploit Acoustic Emission data to estimate crack propagation in solid freight axles by leveraging Self-Organizing Map. They addressed these defect prediction tasks exploiting different AI techniques including: ANN for track deterioration (Lee et al., 2018), SVM for track geometry defects (Hu and Liu, 2016), as well as, Decision Trees (DTs) for both track geometry defects (Sharma et al., 2018) and rails/wheels wear condition (Li et al., 2014). Notably, Sharma et al. (2018) also relied on the Markov Chain and Bernoulli Process to improve the maintenance decision making, while Li et al. (2014) presented another model to also predict the failure alarm activation caused by hot bearings leveraging DT and SVM. In addition, the XGBoost algorithm was used to predict the occurrence of broken rails (Zhang et al., 2020b), a regression model, combined with Image Processing and PCA, was implemented to predict contact fatigue defects (Sysyn et al., 2019a), and a Nonlinear Autoregressive model with exogenous input neural network was exploited to predict rails and wheels defects (Shebani and Iwnicki, 2018). Lastly, an expert system was also built combining fuzzy Takagi–Sugeno interval models to predict squat defects evolution (Jamshidi et al., 2017b).

Failure Prediction. The papers we analysed mostly focused on issues related to tracks and rolling stock. These studies mostly aim to estimate the Remaining Useful Life (RUL) of components leveraging different approaches such as the k-means algorithm and Hierarchical Hidden Markov Models for turnouts failures (Eker et al., 2011), Fuzzy NNs and grey theory for track circuits prognosis (Hu et al., 2019), and Data Streaming Analysis and Support Vector Regression for axle bearings RUL estimation (Fumeo et al., 2015). Also, the same authors in Sammouri et al. (2013) and Sammouri et al. (2014) focused on onboard subsystems failure prediction: in the former, they relied on Null Models-based algorithms and temporal association rules; in the latter, the floating train data were converted in a labelled dataset and analysed through four different ML techniques (K-Nearest Neighbours, Naive Bayes, SVM, and NN) . Worth to mentioning, Sikorska et al. (2011) provided a survey offering a picture on the available approaches to cope with RUL estimation. A hybrid approach which combined Conditional Restricted Boltzmann Machines and Echo State Networks was proposed to predict abnormal situation of tilting system of trains based on the analysis results of discrete-event data (Fink et al., 2013). McMahon et al. (2020) addressed the issue of missing data within mechanisms to accurately predict health condition of railway infrastructure and rolling stock; in that study, advanced models and algorithms for recovering missing data have been evaluated and a procedure was provided to select an appropriate solution under different scenarios.

Maintenance Planning. The Maintenance Planning category encompasses papers which proposed an AI-based approach for decision support systems allowing dynamic scheduling of tracks' maintenance and inspection activities. Different approaches were proposed leveraging various techniques, such as expert decision rules (Guler, 2013), Bayesian Networks (Marsh et al., 2016), and Genetic Algorithms (Khouzani et al., 2017; Guler, 2016) to optimize maintenance activities. In addition, DT, RF, and Gradient Boosted Tree methods were also investigated to predict whether a maintenance activity, and its type, must be performed or delayed at switches (Allah Bukhsh et al., 2019). Differently, Wang et al. (2020c) investigated a Long Short-Term Memory based RNN (LSTM-RNN) approach to predict future maintenance timing of high-speed rail power equipment. Lastly, a Decision Support System was built leveraging CNN and fuzzy model combining data coming from multiple sources (cameras and the Axle Box Acceleration (ABA) system) to estimate the rails health conditions (mostly focusing on rail squats defects) and, then, achieve data-driven maintenance planning (Jamshidi et al., 2018).

Autonomous Maintenance. Papers under Autonomous Maintenance deal with the combination of "Autonomous Systems & Robotic" and "Artificial Intelligence" to obtain intelligent systems able to inspect and maintain railways' components autonomously. The possibility to fuse industrial robots with other techniques/sensors was considered also leveraging CV and ML to identify plugs in trains' frame and, thus, improve maintenance qualities (Vithanage et al., 2017). Furthermore, several supervised ML approaches (e.g. Ensemble Bagged Trees, Stepwise Linear Regression, and Rational Quadratic Gaussian Process) were investigated to analyse the feasibility of introducing autonomous robotic systems for automatic train coupler electric head inspection (Vithanage et al., 2018). Lastly, a solution was presented to ensure that the arm of the cab front cleaning robot autonomously adapts to the surface to be cleaned (Moura and Erden, 2017).

Data source. For Maintenance and Inspection, diverse sets of recorded data were used such as video and images data (e.g. Feng et al. (2014), Trinh et al. (2012), Faghih-Roohi et al. (2016), Wang et al. (2018) and Giben et al. (2015)), and other kinds of records such as data streams by onboard sensors (e.g. Yin and Zhao (2016), Fumeo et al. (2015), Sammouri et al. (2014), Li et al. (2011a) and Rabatel et al. (2011)), audio data (e.g. Carboni and Crivelli (2020) and Lee et al. (2016)), current signals (e.g. Zhou et al. (2016) and Ou et al. (2019)), vibration signals (e.g. Jayaswal et al. (2011), Tsunashima (2019) and Luo et al. (2020)), LiDAR point cloud data (e.g. Tu et al. (2020)) and so on. In some cases, combinations of multiple data sources were also considered; for example, Zhang et al. (2020b) analysed track files, traffic information, maintenance history, and prior defect information, while, Jamshidi et al. (2018) combined ABA and video data.

3.2. Safety and security

To ease safety & security concerns raised by individual trains or even the whole railway system, 11 papers (9% of totally surveyed) have investigated the possibilities of introducing AI-based techniques to complex practical scenarios. For example, risk management, failure/error estimation, and railway accidents, including level crossings accident and station accident.

Risk management. In the context of risk assessment, An et al. (2011) proposed a five-phases model based on the fuzzy reasoning approach and the fuzzy analytical hierarchy decision-making process; additionally, they also employed qualitative measurements to describe frequency, severity and probability of consequences for each hazardous event. Based on the result of this study, Gul and Celik (2018) developed a novel risk assessment approach which combined Fine–Kinney method and fuzzy rule-based expert system to qualitatively identify risk clusters and corresponding control measures. Considering not only the construction expenses & financial cost, but the safety factors, Zhang et al. (2018) utilized the coupled Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and A-star algorithm to tackle the problem of hazardous liquid railway network route selection. Accurately detecting hazardous trespassing of railway tracks is always a hot topic among railway risk management while witnessing these events requires a large volumes of surveillance video data in the railroad industry, Zaman et al. (2019) proposed an AI framework for the automatic trespassing identification in real time, where a Mask R-CNN architecture was built that classifies images captured.

Disruption and anomaly estimation. Track circuit is a train detection device that tells whether a block or section of railway tracks is occupied or not. Multiple papers have researched on the maintenance and failure estimation of it. For instance, Zilko et al. (2016) analysed the factors influencing latency time and repair time respectively and correlations between them and thereby a copula Bayesian Network-based prediction model for estimating the length of a track circuit disruption was developed. Li et al. (2011b) alternatively applied a knowledge rules-based method to simulate the reasoning & deducting process of track circuit coding for a high-speed railway. Correspondingly, the study of Sturari et al. (2017) presented a novel method that mixed visual analysis and point cloud information to effectively detect those surrounding changes that come from the anomaly in the environment (e.g. a falling tree blocking the track or abnormal railway trawlers). Hadj-Mabrouk (2019) presented a Software Error Effect Analysis framework that comprised of a knowledge-based system, a case-based reasoning system and an assessment model towards the safety of critical software.

Railway accidents. Decision Tree has been employed by Alawad et al. (2020) to discover hidden patterns & knowledge among hazardous events that happened at railway stations and predict the behaviour of affected passengers. Ćirović and Pamučar (2013) suggested a decision-making support system for identifying the qualified candidates among a great number of level crossings. Each level crossing would be evaluated and assessed by the proposed Adaptive Neural Fuzzy Inference System and the selected ones would be optimized from passively protected to active system-aid protected.

Data source. In the papers that concern Safety & Security, multiple sources of statistics have been employed such as expert scoring towards risk-related factors matrix (Gul and Celik, 2018), historical accident records (Alawad et al., 2020; An et al., 2011), and vision captures of track defects or surroundings (Sturari et al., 2017).

3.3. Autonomous train driving and train control

Autonomous train driving and vehicle control have been attracting more attention to AI in recent years because they aim to enhance safety and enable a more efficient speed profile. The powerful learning and computation capability of AI have led to serve many goals of Autonomous Driving and Control better, especially train energy efficiency, as well as verification and validation . The problems are present in both metro and mainline railways.

Energy-efficient driving. To tackle energy-efficient driving optimization, approaches are developed based on Genetic Algorithms (Brenna et al., 2016), Approximate Dynamic Programming (ADP) (Wang et al., 2020b), Reinforcement Learning (RL) (Yin et al., 2014) and SVM (Hua et al., 2020). In particular, Wang et al. (2020b) used ADP to learn the costs of energy and time over iterations. While Yin et al. (2014) presented two train control algorithms – an expert system and a reinforcement learning – to operate the train similar to an experienced driver with real-time data to reduce energy consumption whilst maintaining comfort level and punctuality. To realize the safe and efficient control of heavy haul rail systems, Hua et al. (2020) proposed an approach that incorporating blockchain-based Federated Learning and SVM based intelligent control model.

Verification and validation. In verification and validation of railway control, AI can be utilized to learn from the expert knowledge without the presence of an expert (Nowakowski et al., 2018). With respect to big data analysis, Zhang (2017) adopted a model based on the fuzzy Resource Description Framework and uncertainty for different high-speed train control systems.

Data source. Until now, scholars have mostly exploited information on real-life and theoretical characteristics of infrastructures (e.g. road conditions) and vehicle components (e.g. engine) to evaluate the performance of algorithms (Brenna et al., 2016; Carvajal Carreño, 2017; Wang et al., 2020b). Moreover, existing studies mostly collected data from experts' prior knowledge (e.g. from experienced driver) to build and tune ML models (Nowakowski et al., 2018; Yin et al., 2014).

3.4. Traffic planning and management

AI has been applied in various Traffic Planning and Management problems such as timetabling, routing, shunting, capacity management , traffic analysis and prediction, and rescheduling & disruptions management. In addition, one more paper on strategical planning problems have been found addressing track design. The papers on (general) heuristics or pure mathematical programming are not considered, because they are not conventionally regarded as AI. Instead, the Evolutionary Programming/Heuristics and Mathematical Programming using AI are in the scope.

Strategical Planning. In order to optimize the process of railway routing and track alignments especially the three-dimensional alignment in mountainous regions, a genetic step-by-step hybrid Particle Swarm algorithm was constructed by Pu et al. (2019). The study of Hickish et al. (2020) adopted a Genetic Algorithm to proceed the optimization operations of rail networks, a novel Bayesian Optimization model was evaluated against the GA method. The test-tasks for this model involve the allocation of limited number of carriages between trains and the assignment of line speeds around the network.

Tactical Planning. Several tactical planning problems including timetabling, routing and shunting have been addressed. Given that tactical planning problems are normally designed from the perspective of satisfying the existing constraints and optimizing a multi-criteria objective function, scholars normally aim to generate a feasible timetable that ensures the whole track line (or in a station area/depot) to be conflict-free. Numerous AI-based techniques can contribute to simplify this process, e.g. Bio-inspired algorithms (Tormos et al., 2008; Ho et al., 2012), Reinforcement learning models (Khadilkar, 2019; Peer et al., 2018; Salsingikar and Rangaraj, 2020; Ying et al., 2020).

We fully inspected the design objectives of these studies and divide them into two groups: train operator-centred (e.g. Tormos et al. (2008) and Khadilkar (2019)) and quality of service-centred (QoS-centred) (e.g. Schüpbach et al. (2018) and Xue et al. (2019)). The first paradigm aims to generate a feasible timetable that specifies the departure and arrival time for all trains such that they are assigned with required resources (e.g. rail infrastructures and facilities). Whilst quality of service-centred models take passengers' service quality into account, it aims to reduce the total travel time or waiting time when transfers are needed.

To minimize train delays, Barman et al. (2015) developed a heuristic model from the passengers' scope which combines a set of Fixed Path formulations with a Genetic Algorithm, for selecting a least-time-cost path for each train. A Genetic Algorithm was introduced by Tormos et al. (2008). Furthermore, the negotiation process between infrastructure providers and train operators has been modelled as a multi-objective optimization problem according to Ho et al. (2012) to form a track access rights agreement. A step-by-step approach for a new capacity planning paradigm based on service improvement intention was proposed by Schüpbach et al. (2018) and they presented an automatic timetable generation process with GA formulations in the context of the Swiss Federal Railway. To make use of the wasted capacity at a constant departure frequency, a Genetic Algorithm was adopted by Xue et al. (2019) as well, with the objective of finding the optimal solution in a double-routing optimization model. Wang et al. (2019c) developed a continuous multi-objective swarm intelligence algorithm for solving a routing optimization problem and analysing towards simulation results from a quantitative and qualitative point of view.

Additionally, Yin et al. (2018) designed a three-phase heuristic algorithm to address a demand-responsive timetabling problem, while a hybrid performance-based timetabling strategy was used in Goverde et al. (2016) where they selected several performance indicators to evaluate and construct timetables.

In timetabling, a RL algorithm was developed to allocate track resources to each train and optimize departure/arrival time with the objective of minimizing the total priority-weighted delay (Khadilkar, 2019).

Peer et al. (2018), Salsingikar and Rangaraj (2020) and Ying et al. (2020) applied Deep Reinforcement Learning methods for addressing Train Unit Shunting Problem, single-track routing problem, and metro train scheduling. Especially, Peer et al. (2018)

and Ying et al. (2020) trained CNNs using input state representation of shunting yard and metro trains allocations respectively, in order to gain a better performance than exact operation research method.

Traffic Analysis. Statistics for large-scale railway networks exhibit characteristics of considerable amount and multiple formats. Conventional data analysis tools may not perfectly meet the requirements of discovering patterns (from big data) in current railway traffic. Therefore, novel DM analysis tools (Wang and Zhang, 2019; Cerreto et al., 2018; Kecman and Goverde, 2015), evolutionary-based techniques (e.g. Oneto et al. (2017)) have been introduced to accommodate this challenge both in delay analysis and conflict prediction. Liu et al. (2018) developed a complex three-tier DM processing framework for analysing train timetable performance measures (i.e. arrival punctuality or running time of the whole line) through a supervised process. Cerreto et al. (2018) employed a DM technique based on *k-means* clustering to identify substantial delay patterns and summarize the primary cause for each clustered group of delay occurrences. Whilst Wang and Zhang (2019) studied how the factors of weather & scheduled timetable would affect train delays by proposing a gradient-boosted regression tree model. Similarly, Huang et al. (2020) developed a FCLL-Net model that incorporates a fully-connected neural network and two LSTM layers to investigate operational interactions between trains and thus to predict delays. For accurately predicting running and dwell time and train event times and thus expected conflicts, Kecman and Goverde (2015), Kecman and Goverde (2015) developed multiple data-driven approaches such as robust Linear Regression, Tree-based algorithms (Regression Trees, RF) and dynamic arc-weighted event graph model.

Similarly, Oneto et al. (2017) applied big data analysis tools (i.e. deep/shallow extreme learning machine) to build a data-driven train delay prediction system that considers the effects of historical train movements and weather patterns.

More than that, a model that combined ANNs and Multi-Layer Perceptron approaches to predict the arrival time for freight trains has been proposed by Prokhorchenko et al. (2019). To estimate arrival times for freight traffic on United States railroad, Barbour et al. (2018) proposed a data-driven system to predict times of arrival for individual freight trains based on the properties of them, which compared the performance of multiple supervised ML models.

The study of Zhuang et al. (2016) addressed the gap between a traditional approach and a novel solution to conflict prediction problems by employing a temporal fuzzy reasoning method. Differently, a simulation-based approach for optimizing the parameters of train dynamics equations and a program for train length estimation were proposed by Bešinović et al. (2013), which aimed to design a reliable train running time model.

Rescheduling and Disruptions. Multiple studies have investigated rescheduling problems for disturbance and disruption of services, and have proposed solutions based on bio-inspired methods (e.g. Wang et al. (2019b)) and reinforcement learning (e.g. Obara et al. (2018), Semrov et al. (2016) and Roost et al. (2020)). The distinctive objectives can be identified as train-oriented and passenger-oriented as well. The former commonly considers reducing differences between the scheduled timetable and actual rescheduled timetable and thus minimizing total/primary/knock-on delays of trains (e.g. Wang et al. (2019b)), and the latter — maximization of quality of services for passengers or passengers' satisfaction (e.g. Obara et al. (2018)).

A GA-based PSO method was proposed by Wang et al. (2019b) to reduce the sum of secondary delays and the number of trains whose delay overpass a preset threshold. Differently, a new train timetable rescheduling model was presented by Kuppusamy et al. (2020), which combines the Improved Genetic Algorithm and LSTM-RNN, but with the aim of reducing power utilization by adopting the entire benefits of reproductive braking energy under a random situation. Expert systems/knowledge-based decision support systems have attracted significant dispatchers' attention recently due to their characteristic of lowering computation time dramatically. The proposed models typically use cost functions based on sum of total delays of the train (e.g. Schaefer and Pferdmenges (1970), Deng et al. (2018) and Fay (2000)). Regarding RL approaches, Deep Q-network method and DRL approach were proposed in the studies of Obara et al. (2018) and Ning et al. (2019), where an agent is responsible for adjusting running time and generating instructions of departure sequences, aiming to maximize passengers' satisfaction and minimize the average total delay for all trains along the railway line. And Roost et al. (2020) used a model-free Asynchronous Advantage Actor-Critic RL algorithm (developed by Google Deep Mind (Babaeizadeh et al., 2017)). In addition, in the work by Semrov et al. (2016), Q-learning is applied to reschedule trains under disruptions on a single track in a real-world scenario in Slovenia. The empirical results demonstrate that this Q-learning based method can produce rescheduling solutions that are at least equivalent and often superior to those of several basic rescheduling methods (e.g. First In First Out – FIFO – and random walk).

Differently, Zheng et al. (2014) built a hybrid bio-geography based optimization algorithm combined with differential evolution to minimize the weighted delivery time in the problem of disaster relief supply operations.

Data source. For Traffic Planning and Management various historical data have been used such as realized traffic movements (Oneto et al., 2017; Khadilkar, 2019), infrastructure occupation data (Kecman and Goverde, 2015; Bešinović et al., 2013; Ho et al., 2012; Schüpbach et al., 2018; Goverde et al., 2016), historical weather records (Wang and Zhang, 2019), existing train scheduled timetables (Deng et al., 2018; Wang et al., 2019b; Huo et al., 2016), topology of rail network (Zheng et al., 2014), and accident event data (Fink et al., 2013).

3.5. Passenger mobility

As we defined in Section 1, Passenger Mobility generally refers to the acts of moving people by means of transportation systems. Providing satisfactory passenger mobility is the final goal of rail transport. In the context of this sub-domain, an important topic is the analysis of passengers' demand as to predict flows, both in mainlines and urban railways.

Flow prediction. Many ML approaches, such as supervised learning paradigms (e.g. Heydenrijk-Ottens et al. (2018)) and DL architectures (e.g. Liu et al. (2019)) are proposed to improve the prediction accuracy. Particularly, the deep learning method is the hot spot of the application (e.g. Xu et al. (2004) and Zhu et al. (2018)). Specifically, Gallo et al. (2019) predicted metro on-board passenger flows by implementing feed-forward ANNs and selected the best-performing ANN structure for each case study based on the analysis. Similarly, Zhu et al. (2018) performed the same technique to predict the entrance and exit passenger flow, but with a comprehensive influential factors analysis in advance. Differently, Xu et al. (2004) executed ANN to unravel the influence of spatial characteristics in predicting passenger flow. However, feed-forward ANNs have drawbacks like parameter sharing and inefficiency towards time-series data. Hence Liu et al. (2019) applied the LSTM-RNN and developed an end-to-end passenger flow prediction architecture that integrated the domain knowledge and deep learning. Additionally, Zhang et al. (2020a) proposed a combination of graph convolutional networks and three-dimensional CNN for (inflow and outflow) passenger forecasting at railway stations, while Velastin et al. (2020) focused on detecting, tracking, and counting passengers getting on/off a metropolitan train by investigating, among others, DL-based object detectors such as Faster R-CNN and YOLOv3. In contrast, Heydenrijk-Ottens et al. (2018) leveraged supervised learning methods to predict and classify the passenger load categories.

Data source. Most commonly historical ridership has been used for the passenger flow prediction (Heydenrijk-Ottens et al., 2018; Zhu et al., 2018; Xu et al., 2004). This historical ridership data could be derived either from smart card transactions (e.g. Heydenrijk-Ottens et al. (2018)) or tickets (e.g. Xu et al. (2004)). Whereas the long collection time of smart card data could hinder the passenger flow prediction in the short-term, Liu et al. (2019) forecast the passenger flow on-board based on the passenger counts at station turnstiles, which could be retrieved in near real-time.

3.6. Summary and discussions

Maintenance and Inspection. According to the findings, researchers have focused their attention greatly on Maintenance and Inspection tasks with about 57% of the total reviewed papers. One of the main reasons for this is the general trend to move from corrective or preventive maintenance to predictive in order to reduce the overall maintenance costs. In essence, given the amount of new data available, the aim is to move towards data-driven methods relying on historical and/or real-time data in order to diagnose faults/defects to predict and avoid possible failures. AI techniques allow maintenance engineers to carry out inspection and diagnostic activities more efficiently in terms of costs, time and accuracy in defect detection, also supporting dynamic activity planning and maintenance automation.

The most involved AI technology in Maintenance and Inspection is Machine Learning. Traditional ML approaches (e.g. SVM, DT, Regression algorithms, ANN, etc.) have found great applicability when dealing with tabular (and possibly labelled) datasets (e.g. Sammouri et al. (2014) and Sharma et al. (2018)), which, in some cases, can also be obtained starting from images (e.g. Gibert et al. (2015) and Liu et al. (2016)), or different kinds of signals like current signals (e.g. Zhou et al. (2016)), vibration signals (e.g. Tsunashima (2019)) or audio signals (e.g. Lee et al. (2016)). After pre-processing steps, numerical features are extracted, and traditional ML model were built. Second to that, Deep Learning has also been widely involved, mostly to build CV applications for Defect Detection and Prediction tasks, where video and images are the most exploited source of data (e.g. Wang et al. (2018), Wei et al. (2019) and Santur et al. (2017)). Lastly, as for the traditional ML techniques, DL-based approaches are also used to analyse tabular data for both classification problems (e.g. CNN architectures Krummenacher et al., 2018) and temporal dependencies analysis (e.g. RNN architectures de Bruin et al., 2017).

The above techniques, together with other Big Data, Data Mining and Pattern Recognition approaches have also been involved in Fault Detection, Fault Diagnosis and Failure Prediction tasks. It is also important to underline the modularity of all the techniques that can be involved in a DM or Pattern Recognition process. There are different techniques for data processing (e.g. Image enhancement for video data), feature selection or dimensionality reduction approaches (e.g. PCA) and data analysis methods to extract knowledge (e.g. ML techniques). All approaches we investigated focused on finding the most appropriate combination of AI techniques for a given problem; most of them tackled similar issues with different approaches depending on available data and data processing requirements.

However, collecting sufficient and qualitatively good data is not always possible. In fact, in many cases, data augmentation techniques, i.e. retrieving more data from those available through artificial and synthetic transformation, have been used to obtain enough training samples to adequately characterize the models.

Therefore, since data is often the main challenge when dealing with AI-based approaches, as future works most of the authors aim to improve their research by analysing more data (e.g. Eker et al. (2011)), using more sensors (e.g. Liu et al. (2016)), improving data quality (e.g. Tsunashima (2019)), testing their models on on-field data (e.g. Shebani and Iwnicki (2018) and de Bruin et al. (2017)), adapting the proposed approach to new kind of data (e.g. Trinh et al. (2012) and Guler (2013)), considering multiple data sources (e.g. Zhou et al. (2014)), etc. Actually, it is worth mentioning that some steps in combining multiple data sources (e.g. Jamshidi et al. (2018)) and different ML approaches in a multi-task learning scenario (e.g. Gibert et al. (2017)) have already been performed.

At the same time, Expert Systems were exploited in this subfield to predict failures and defects (e.g. Jayaswal et al. (2011) and Jamshidi et al. (2017b)), and also, beyond other ML-based approaches, to create decision support systems allowing dynamic scheduling of tracks' maintenance and inspection activities (e.g. Guler (2013)). So far, limited work has been done in this direction, then, as further developments, improved rules and more optimized features can be considered, as well as an in-depth integration with other AI technologies and applications. Lastly, it is also important to underline that some initial steps have been taken towards maintenance automation; different approaches have been proposed or investigated in order to combine Autonomous Systems and AI to obtain intelligent autonomous systems able to inspect and maintain railways' components (e.g. Vithanage et al. (2017) and Vithanage et al. (2018)).

Traffic Planning and Management. AI innovations in the sub-field of Traffic Planning and Management have been a major focus of the research investigated, constituting about 25% of the reviewed papers.

Most rail traffic planning and management problems are formulated as optimization problems where most of them also involve discrete variables, making the problems NP-hard. While exact methods such as branch-and-bound and branch-and-price can find high quality solutions but are often limited by problem size (Alfieri et al., 2006; Lin and Kwan, 2016). Traditional heuristics with or without evolutionary features such as Local Search, GA, Ant Colony, and Particle Swarm are thus used to solve larger traffic planning and management problems as a compromise (Li et al., 2021; Wang et al., 2019b). The disadvantages of these evolutionary methods are that they usually cannot guarantee solution quality and are less robust. Machine Learning based optimization solution methods may give a promising direction in the future, with the advantages of both exact and evolutionary approaches (Bengio et al., 2021).

Conventional ML models (e.g. Regression Trees, RL algorithms), as an addition to the Bio-inspired algorithms we recognized above, are also widely adopted in some related articles. These algorithms have provided strong support for solving rescheduling problems (e.g. Obara et al. (2018)), timetable design (e.g. Khadilkar (2019)), and train routing (e.g. Salsingikar and Rangaraj (2020)). Furthermore, they are effective within big data analytics to identify delay patterns and to estimate delay levels for both passenger railway lines and freight networks (e.g. Wang and Zhang (2019), Prokhorchenko et al. (2019) and Barbour et al. (2018)). Using intelligent knowledge-base reasoning and decision making system to support the procedure of train rescheduling (e.g. Schaefer and Pferdmenges (1970)) would achieve a higher operational efficiency.

The techniques listed above, together with Pattern Recognition and Data Mining approaches were applied to different extents according to the type of target problems. For example, systematic data processing & cleaning frameworks, such as feature engineering, clustering or encoding of time-series data are likely to be adopted against a background of hybrid large-scale data resources (e.g. the data asset with train performance measures and automatic train supervision data combined). This pattern has been found in the papers we reviewed especially in the cases of delay analysis and conflict prediction (e.g. Liu et al. (2018)). Whilst, a rescheduling problem is all about finding a feasible timetable for train operators after disruptions occurred and this may require previous experiences in dispatching (e.g. Deng et al. (2018)), Expert Systems seem to be an effective alternative to manual operations.

All in all, different approaches show their potentials variously in different application scenarios. It is difficult to outline which approach is the most promising one among the railway industry even in the domain of Traffic Planning and Management. It largely depends on the requirements of processing data and the purpose of studies. However, in the applications of ML, RL methods are still in their early stage and require further development for satisfying a more complex industrial/business need. Limited work has been done in the direction of NLP, CV & IP so far. The possibility of incorporating these AI applications into future research strategies should be seriously investigated. Additionally, future research should focus more on model optimization, as well as algorithm improvement with incorporating new indicators or parameters into it, especially the models of ML and DM. To yield better performance and receive a higher accuracy, using hybrid models should be considered.

Safety and Security. The capability to employ AI as an alternative solution in the sub-domain of Safety and Security has been partly explored in the reviewed papers. These papers make up approximately 9% of the total number of the reviewed papers.

So far, including expert systems (e.g. fuzzy reasoning system An et al., 2011), Bio-inspired methods (e.g. PSO, ACO) were genuine attempts on Risk management. The aim of them is typically to quantitatively evaluate the risk score for each physical site and thus invest the limited resources to the most needed areas and reduce general safety cost (e.g. An et al. (2011) and Gul and Celik (2018)). Hazardous events happened randomly with their own spatial and temporal characteristics, and even it is difficult to estimate the severity of consequences. To quantitatively discover danger clusters seems to be a challenging task for classical ML algorithms (e.g. supervised learning models) and DM. Due to an existing huge variation in the quantity of samples among different levels of risks—the amount of small-risk cases largely surpasses that of severe danger conditions. Where the latter ones may not be recognized by a less-trained model. Alternatively, rule-based and case-based reasoning systems can be combined in the future to work as a more ‘experienced’ decision maker for allocating safety resources. CV & IP, with its high level of automation, and solid detection accuracy on practical scenarios, has largely engaged with the procedure of discovering, detecting and identifying anomalies in the environment (e.g. Sturari et al. (2017) and Hadj-Mabrouk (2019)). The applications of these techniques generally incorporate cloud information for analysing.

Autonomous Driving and Control. The combination of AI and Autonomous Driving and Control has shown its potentials with its promising applicability, particularly using reinforcement learning (e.g. Yin et al. (2014)). So far, scholars mostly prove the usefulness of the vehicle control algorithms by using theoretical simulations combining real-life infrastructure and theoretical engine characteristics. However, the real-life train operating conditions are impacted by multiple factors such as wear of rail/wheel contacts, weather conditions, unexpected disruptions or perturbations. Thus, these theoretical simulations (current approaches) still cannot be compared with practical real-life tests, which may raise criticisms towards applicability in real environments. The paper of Wang et al. (2020b) using Approximate Dynamic Programming presents an exception as it introduced the stochastic change of traction force and train resistance.

Additionally, the current models typically consider basic signalling systems, while no applications on advanced systems like ETCS (European Train Control System), are currently existing. This makes the current models not ready for applications because train operation does not comply with the railway signalling system and respect the speed restrictions and the movement authorities. One of the future avenues of this field could further explore GAs and RL with a special focus on signalling system-compliant autonomous driving and control to safeguard safety.

Regarding non-vital control systems, only limited research exists. For example, the use of image data has shown its capabilities in controlling the pantograph with the Deep Learning technique. Besides, the Expert System can grant invaluable knowledge without the presence of an expert in certain control fields. However, the number of studies in this non-vital AI-related control domain is still comparably scarce, which implies a future direction to explore the effectiveness of AI.

Passenger Mobility. AI innovations have shown their significance in addressing the problem of passenger flow predictions (Gallo et al., 2019; Heydenrijk-Ottens et al., 2018; Liu et al., 2019; Zhu et al., 2018; Xu et al., 2004). These predictions mainly focus on the short-term prediction tasks. Particularly, scholars are in favour of applying DL paradigms to perform the passenger flow predictions (e.g. Gallo et al. (2019), Liu et al. (2019), Zhu et al. (2018)). Compared to other learning paradigms which are normally set as the baseline models (e.g. Linear Regression), DL outperforms them with a considerable margin by unveiling the non-linear relationship (Liu et al., 2019; Zhu et al., 2018). Yet, comparing the results across the studies can be difficult at this moment due to several reasons. First, every DL architecture needs a well-knitted feature set that is extracted from the input data and this extraction differs from one case study to another due to its influence. This makes the availability, effectiveness of selected attributes, and expected output of data vary between different models. Second, the metrics that the researchers chose to evaluate the precision of the prediction are not entirely similar (e.g. R^2 from Liu et al. (2019) and Root Mean Square Error from Zhu et al. (2018)), which passes the challenge to interpret the results against each other. This indicates that a set of universal and complete metrics is needed and could be defined. Moreover, one of the directions that could be further explored is to propose an architecture of feature selection and data consideration such that the consistency and convenience of the feature set construction can be guaranteed, for example, spatio-temporal and operation characteristics (Liu et al., 2019).

Also, historical data (e.g. smart card data retrieved from the Automatic Fare Collection system) has been extensively applied to predict the passenger flow as one of the sound bases. However, Although the majority of the papers we found focus on long-term predictions, it is important to highlight that historical data can be used for real-time predictions (Li et al., 2020). To this end, incorporating or leveraging other data that could be retrieved in (near) real-time to predict the ridership is another research possibility (Gallo et al., 2019).

Adopted AI Algorithms/Models. Table 6 reports the AI approaches used in literature to address problems within railway sub-domains. Diverse techniques have been adopted and some "clusters" may be identified: in the context of Maintenance and Inspection, approaches have been tested including Neural Networks and Instance-based techniques that seem not to be so deeply investigated in other sub-domains; the same holds for Evolutionary Computing, which has been mostly used for Traffic Planning and Management. Considering these fragmented (or crowded, depending on the subdomain) scenarios, it would be essential to have some general guidelines for the selection of AI approaches, especially in industry. To that aim, in RAILS D1.3 (2021), guidelines indicating the most suitable AI approaches to be chosen given a specific set of data, the tasks to be solved, and the required responsiveness (i.e. if the model has to be run in real-time or not) have been outlined.

Generally, we find two patterns when linking AI approaches to rail sub-domains.

First, there are certain popularity/compatibility relationships among AI approaches and rail sub-domains, that some AI approaches are found in most sub-domains while others only appear in a limited number of rail areas, and vice versa. See Table 6 for a detailed illustration.

Second, the development and implementation of AI approaches are at various stages in terms of maturity in different rail sub-domains.

For instance, Neural Networks are found in all rail sub-domains which is understandable due to the wide range of problems they can deal with. Evolutionary Computation is only found in fewer areas (mostly in Traffic Planning and Management). This is because EC mainly aims at solving optimization problems which are the most common type of modelled problems in Traffic Planning and Management. Regression and Clustering are the least found among the rail areas. The former, as a traditional method, may have limited capabilities in handling emerging and challenging problems, while the latter has restricted application scenarios where there is a need for clusters without any labelled data.

Notably, the Maintenance and Inspection sub-domain is extremely advanced in terms of AI applications that have been tested (also on the field) in respect to other sub-domains (RAILS D1.3, 2021). The practical integration of AI in scenarios involving safety concerns as the main aspects to be ensured in real-time (e.g., Autonomous Driving and Control and traffic rescheduling) is still far to be achieved given, among others, the non-stable behaviour and opacity of some AI approaches. Therefore, these sub-domains still do not see real-life AI applications. Also, there are cases in the Safety and Security sub-domain (e.g., accident prediction) in which data (or properly structured data) are missing or are not enough to properly train AI systems given the rarity nature of the events to be analysed. Similarly, the practical implementation level of the listed technologies in the scenarios of delay time prediction and real-time timetabling/rescheduling is mostly in the theoretical stage. At present, it can be seen that AI-related applications, such as Evolutionary Computing and Neural Network-based models, have not been greatly put into practice, and the relevant commercialization cases are rare.

4. Future directions

Based on the review presented in this paper, several upcoming research directions relevant to the academic and professional communities in AI and railway transport have been identified as follows.

Dealing with data quality. Providing good quality data has always been one of the main challenges in characterizing AI models. Indeed, although AI models are generally capable of extracting knowledge from almost every kind of data, it is possible to increase their performances by using good quality data, i.e. those expressing relevant information to tackle a given task. Focusing only on

Table 6
Overview of AI algorithms and models used in specific railway sub-domains.

Railway subdomain		Maintenance and inspection						Safety and security			Autonomous driving and control		Traffic planning and management				Passenger mobility
Focused area		Defect detection	Fault detection and diagnosis	Defect prediction	Failure prediction	Maintenance planning	Autonomous maintenance	Risk management	Disruption and anomaly detection	Railway accidents	Energy-efficient driving	Verification and validation	Strategical planning	Tactical planning	Traffic analysis	Rescheduling and disruptions	Passenger flow prediction
AI Algorithms/Models: Tree-based	DT			x		x				x					x		
	RF	x				x									x		x
	GBDT					x							x		x		x
	EBGT						x										
Inst.-b	SVM	x	x	x	x						x						
	SVR				x												
	KNN				x												x
Bayesian	NB				x												
	BN					x			x								
	LaDA	x															
Regres.	LR														x		
	SWLR						x										
	GPRRQ						x										
Neural networks	MLP																x
	ANN	x	x	x	x												x
	FNN				x					x							
	NARXNN			x													
	CNN	x	x			x			x		x				x		x
	RNN		x		x												
	LSTM-RNN					x									x	x	x
	DBN		x														
	RBM				x												
	R-CNN	x															x
Cl.	K-means				x										x		
	EM		x														
Other	AdaBoost	x															
	XGBoost			x													
	LDA	x	x														
	QDA		x														
	FRA							x							x		
	FAHP							x									
	KRB								x		x	x					
	ADP										x						
	RL										x			x		x	
	HHMM				x												
EC	GA					x					x		x	x			
	PSO							x					x			x	
	SI													x			
	ACO							x									

Inst.-b: Instance-based; **Regres.**: Regression; **Cl.**: Clustering; **EC**: Evolutionary Computing
Decision Trees (DT), Random Forest (RF), Gradient Boosting Decision Tree algorithm (GBDT), Ensemble Bagged Trees (EBGT), Support Vector Machine (SVM), Support Vector Regression (SVR), K-Nearest Neighbour (KNN), Naive Bayes (NB), Bayesian Networks (BN), Latent Dirichlet Allocation (LaDA), Linear Regression (LR), Stepwise Linear Regression (SWLR), Rational Quadratic Gaussian Process Regression (GPRRQ), Multi-Layer Perceptron (MLP), Artificial Neural Networks (ANN), Fuzzy Neural Networks (FNN), Nonlinear Autoregressive Network with Exogenous Inputs Neural Network (NARXNN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-term Memory Recurrent Neural Network (LSTM-RNN), Deep Belief Network (DBN), Restricted Boltzmann Machine (RBM), Region-Based CNN (R-CNN), K-means algorithm (K-means), Expectation–Maximization Algorithm (EM), Adaptive Boosting (AdaBoost), eXtreme Gradient Boosting (XGBoost), Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Fuzzy Reasoning Approach (FRA), Fuzzy Analytical Hierarchy decision making Process (FAHP), Knowledge Rules-Based (KRB), Approximate Dynamic Programming (ADP) Reinforcement Learning (RL), Hierarchical Hidden Markov Models (HHMM), Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Swarm Intelligence (SI), Ant Colony Optimization (ACO).

the quantity would be not enough as large datasets, both in terms of features and entries, do not always lead to better performance. Most of the studies focused on proprietary datasets, built from scratch to cope with a specific task. Despite being a suitable solution, as the dataset is an integral part of an AI model, there is a lack of knowledge sharing leading to two main issues when addressing a given problem: (i) each study may focus on a set of characteristics that could differ from those identified in another study; (ii) each study may leverage on a subset of data which may differ from that used by another study. Therefore, it would be needed to publicly provide new standardized datasets specific for the railway sector, encompassing a specific set of features and samples (possibly in agreement with railway stakeholders and agencies), to build up reliable benchmarks and help to improve current and new research. In practice, our suggestion is to create datasets such as ImageNet (Deng et al., 2009) or MS COCO (Lin et al., 2014), that have been extremely useful for computer vision applications. However, it is worth mentioning that Pappaterra et al. (2021) have recently carried out a systematic review on AI public datasets for railway applications, which can be used to test and compare the effectiveness and efficiency of AI models. Other relevant aspects would be to use data collected in real-time to address, for instance, Passenger Mobility tasks such as passenger counts at station turnstiles (Gallo et al., 2019), and use data collected from trials and real-life experiments, as these data will better describe the behaviour of the phenomena. For instance, in the sub-domain of Autonomous Driving and Control, the real-life running of vehicles could be impacted by multiple real-life factors, which need to be captured. Lastly, another challenge that may be arising is protecting the privacy of business data (e.g. transport operators or maintenance companies) in open market railway systems. To address it, new concepts like Federated Learning (Yang et al., 2019, also known as collaborative learning) can become useful tools to allow processing data locally at each company's own IT facilities, so that it will be possible to share all the pieces of knowledge contained in the various datasets while keeping them private.

Dealing with limited/imperfect data. Next to data quality, data quantity is also one of the crucial aspects because in many cases only limited data is available. On the one hand, Transfer Learning (Pan and Yang, 2010) approaches can be used to achieve good performance even on "small" datasets; on the other, a "sufficient" amount of data should be collected to allow optimal characterization of AI models. However, there are cases where data collection is not trivial, such as accidents, safety-critical systems failures, or "rare events". In such cases, digital models (including digital twins) can be used to generate synthetic data; otherwise, data augmentation methods both traditional, such as rotation and resizing, and advanced, such as Data Augmentation Generative Adversarial Networks (Antoniou et al., 2017), can be exploited to synthetically generate new data. In addition to insufficient data, data heterogeneity is also a concern. In fact, Machine Learning algorithms expect homogeneous data as input, and do not perform well on understanding nuances over a variety of data formats. A critical challenge is to develop an algorithm to convert data in a way that appropriate interactive analysis can be conducted. Attoh-Okine (2014) provided an example showing that rail defects data and geometry data are not homogeneous, hence they need to construct proper interactions between the two types of data for downstream AI models.

Dealing with uncertainty. There are many uncertainties and gaps within ML approaches, such as the uncertainties arising from data collection in a specific domain, the variances in a specific type of data, and the imperfection of the models. On the one hand, uncertainties and gaps in the data are often difficult to be addressed using traditional techniques, such as a complex non-linear relationship between the variables (e.g. internal and external characteristics of the railway system) and the target (passenger flow) or train trajectory optimization with parametric uncertainty. On the other hand, there are uncertainties, errors and missing values associated to data collection procedures; see for example, McMahon et al. (2020) for approaches to dealing with missing data and Jagadish et al. (2014) for the proposed data uncertainty solutions regarding video surveillance and inspections for vehicle/track maintenance. Information from different databases may be incomplete and inconsistent, even due to subjective judgements, therefore another challenge to address is the subjective information encountered during data collection, which can be addressed by introducing a universal analysis paradigm. To this end, AI can leverage the probability to harness and handle these uncertainties and model a relationship between the cause and effect of different real-life scenarios by combining the available data with assumptions (Denœux et al., 2020).

Human-in-the-loop Machine Learning. Human-in-the-loop Machine Learning is such an emerging tool that incorporates human opinions into the ML process, which not only strategically improves the ceiling of performance for machine learning models but also accelerates the process of reaching expected accuracy (Monarch, 2021). Annotation and Active Learning (AL) are two representative paradigms for human–computer interactions in Human-in-the-loop Machine Learning (Pandey et al., 2022). Annotation is defined as the procedure of adding more label information to raw data (e.g. images without descriptions, speeches or texts without sentiment judgements) (Monarch, 2021). AL can be seen as a process of determining which data to sample for human annotation (Budd et al., 2021). In many cases, especially when the characteristics of the data are ever-changing over time and places, annotation is commonly used as a complementary technique to improve model performance by labelling more training data (e.g. Sacha et al. (2017)). Human annotation would be regarded as an effective practice to assess the ceiling of model performance, not only because it boosts the traditional pattern of adapting new algorithms when application scenario changes, but it alternatively focuses on how to transfer labelling strategies to an existing model and thereby create more available data. AL strategies can be helpful where railway decision makers need to take actions within a limited time. Additionally, AL is able to select the most suitable data and using iterative feedback to steer models to optimality for a given prediction (e.g. traffic flow prediction, predictive maintenance actions) and offering understandable ways to interpret and respond to predictions. For example, incorporating different formatted sensory data from multiple on-board sensors and choosing the best ones might be a challenging task without AL in the study of Zhang et al. (2015).

Computer Vision for Safety and Security. Computer Vision includes powerful methods and models to analyse the environment and act in response to its mutation. We have seen numerous contributions related to the application of computer vision for maintenance and inspection purposes. However, CV applications, from motion tracking to intrusion (video surveillance) and obstacle detection, could have a great impact on safety, security, and passenger crowd characterization in both railway stations and workplaces. Considering Shift2Rail projects, some steps have already been taken in these directions by focusing on crowd analysis at railway stations (e.g. FAIR STATIONS), fare evasion detection (e.g. TRAINSFARE), and the improvement of workers' safety during inspection activities through IoT devices and CV (e.g. ZIMASS). These topics, together with others such as video surveillance of the environment around tracks and level crossings and the prediction of passengers and rolling stock behaviour, could be interesting applications for further investigations. In many cases within railways, CV can leverage on existing installation of (possibly smart) CCTV cameras required for operator-based for safety monitoring and security surveillance (e.g. in stations or at level crossings). Even if required cameras are not already installed, their installation or upgrade of existing installations requires lower costs and efforts compared to other kinds of sensors. Furthermore, cameras enable a set of future developments and applications such as, trespassing, on track object detection, and increasingly complex physical threat scenarios, possibly in combination with diverse sensors (Flammini et al., 2013).

Applying NLP to non-structural data. Recently, NLP strategies have been widely utilized to optimize the process of transforming unstructured or hybrid information into a well-formatted one. NLP techniques are able to effectively extract essential knowledge from these reports and messages and make it available for the further modelling process. For example, NLP can be used for maintenance. Originally, historical maintenance records presented unstructured or semi-structured documents, As such, these records can be successfully processed by NLP to determine the most critical components, which can further lead to determining optimal maintenance strategies (Edwards et al., 2017). For example, Runeson et al. (2007) uses NLP to detect duplicate defect reports at Sony Ericsson Mobile Communications. Also, Serna and Gasparovic (2018) discussed the potential in applying big data and text mining technologies from social media to help policymakers in transport analysis and policy making, including NLP as a powerful tool for text mining and analysis. These articles concern about generic transport policy making, and there is no reason that railways, as an important sector of transport, would be excluded from this potential direction. For instance, by analysing the information extracted from train operators' official websites and tweets, and the tweets from customers, policymakers can respond accordingly. In addition, NLP could be exploited in Passenger Mobility, to monitor and evaluate passenger satisfaction from the textual perspective.

AI in decision making problems. Machine Learning and Deep Learning are not the process of decision-making themselves, but they can be incorporated to support the optimization of larger and more complex combinatorial models, such as network planning, crew scheduling, locomotive fleet sizing (e.g. Powell et al. (2014) and Morabit et al. (2020)). Further, one of the limitations of bio-inspired approaches (e.g. Evolutionary Algorithms) is that they do not guarantee they will find the optimal solution (decided by the nature of them). That is, the overall quality of solutions cannot be guaranteed, and it has to be benchmarked against other exact optimization methods, such as mathematical-based models. There has been an impressive advance in solving combinatorial optimization problems by Mathematical Programming and ML (Bengio et al., 2021). This implies that there is great potential in solving railway planning and scheduling problems using AI-aided optimization approaches given the fast-growing research interests in the theoretical optimization community.

Multi-agent systems & Negotiations. As a specific application of Distributed Artificial Intelligence, the aim is to improve flexibility, capacity and resilience of the railway system as a mobility backbone, to accomplish an efficient and demand-aware urban and interurban rail mobility growth. For example, Cesme and Furth (2014) explored a new paradigm for intelligent traffic signal control — 'self-organizing signals', based on dynamic coordination rules within a group of closely interacted agents. The result shows that overall delay has been reduced significantly. It is interesting to further discuss the feasibility of transferring such a paradigm to the railway traffic signal system and even the rescheduling problems. In addition, some new frameworks, such as the multi-robotic system (Whitbrook et al., 2018), could be implemented to automate and accelerate business communications between Infrastructure Manager and Train Operating Company, such that various agents in this system (e.g. trains) will be able to interact and negotiate with other agents. This would benefit dynamic online reprogramming and coordination of actions in real time.

Intelligent Cybersecurity and AI. Intelligent cyber threat defence is an edging solution nowadays that gathers raw data about emerging or existing threat performers from multiple sources (Cascavilla et al., 2021). These data then would be analysed and filtered to produce original threat feeds and management reports that contain information, aiming at automating security control process and identifying potential cyber attacks in a more accurate and faster manner. Like any other industrial sector using automated control systems, railways will have a technical challenge to fight against cyber-threats and protect their assets. According to Liu et al. (2018), the intelligent networking of mobility collects a large amount of data from sensor monitors and mobility apps in an ever-growing manner. Obviously, these data contain massive quantities of sensitive and personal information. Cyber-attacks from hackers, criminal organizations or intelligence services are prone to undermine the security and integrity of these data. Relevant studies and innovations in the context of AI-aided cybersecurity in the railway sector have been launched in recent years but it still requires more development (Kour et al., 2019). At this stage, fast-growing connections between the railway system and its customers have been established in different services and applications, especially on the traffic management and intelligence maintenance sides—such as intelligent passenger information systems (Gallo et al., 2019), predictive maintenance capabilities (Wang et al., 2018), enhancement of train punctuality (Barman et al., 2015), improvement of track capacity (Xue et al., 2019), and identification of the weakness regarding unexpected disruptions (Yin et al., 2022). However, it is shown that conflicts between railway automation and data safety of these procedures were not well-explained among the studies mentioned above. For example, Bayesian Network approaches can be adopted for quantitative threat assessment (Pappaterra and Flammini, 2019). In addition, one can consider extending the conventional risk assessment method from a strategical perspective, in order to incorporate a wider set of procedures related to cybersecurity concerns (Mokalled et al., 2019).

Combined AI approaches. In many cases, AI-based applications have achieved good results in extracting information from data and make predictions, pattern recognition, automation procedures, and so on. What is also interesting, is combining multiple AI approaches to better cope with a given task, such as image processing techniques to extract features from video data and traditional ML techniques, e.g. regression models (Sysyn et al., 2019a) to make predictions. These approaches can be quite similar, as the series of classifiers implemented by Trinh et al. (2012), or different, as presented by Fink et al. (2013) who combined Conditional Restricted Boltzmann Machines and Echo State Networks. However, combining multiple approaches, each of which focuses on a specific facet, can lead to a better characterization of the scenario and then to improved performances. Beyond that, DL is a black-box technique, thus lacks explainability. Therefore, the combination of traditional machine learning and deep learning to better investigate the causality and utilize multi-source data could be very useful (Omta et al., 2020). Lastly, one can build AI models for automatic train control that learns offline (e.g. using historical train trajectories) and also adapts dynamically online (e.g. due to real-time conditions of engine, delay, weather, traffic) (Wang et al., 2020b).

AI and revenue management. Revenue management is becoming an important topic in the railway industry, and will attract more attention in the coming years. In addition, AI can be leveraged because of the newly available data. For example, the airline industry is one of the industries on which most studies have been done during the past decades, in order to analyse revenue maximization. AI can be used e.g. for ticket price prediction (Wang et al., 2019a), or seat booking control (Shihab et al., 2019).

5. Conclusions

This paper provides a comprehensive review of state-of-the-art papers addressing the application of AI in the railway industry. Unlike the existing surveys, we address research papers from a holistic AI and railway perspective, covering a broad range of AI fields and seven railway subdomains in Maintenance and Inspection, Safety and Security, Autonomous Driving and Control, transport planning and management, Revenue Management, Transport Policy and Passenger Mobility. As such, it represents a first step towards the adoption of AI in the railway domain by providing an in-depth summary of the current research focuses. In addition, we determine some promising research directions to provide further uptake of AI in railways.

The main scientific research efforts published in the surveyed papers have been seen in the railway subdomain of Maintenance and Inspection (58%), followed by Traffic Planning and Management (24%). Sub-domains of Safety and Security, Autonomous Driving and Control and Passenger Mobility received only limited attention (each under 10%), while no research is found on railway Revenue Management and Transport Policy based on AI.

We provide some observations from our survey. First, AI has already shown a strong impact on a variety of prediction-related work. For example, in the sub-domain of Maintenance and Inspection, AI-enabled failure/defect predictions have been widely investigated. Similar situations are also found in areas such as flow predictions in railway passenger mobility and traffic state prediction in real-time traffic management. Second, the use of intelligent systems tends to provide additional support in improving maintenance operations leading to increased safety. Third, AI can also support optimization models to tackle large-scale real-life problems in scheduling, traffic management, maintenance and inspection planning. Finally, AI applications can use a wide range of data from sensors, visual images/footage, and traffic movement logs, which makes the possibilities of AI in railways extremely diverse.

Overall, these observations suggest that AI, although being at an early development stage in most railway subdomains, is attracting an increasing interest, and therefore it can be easily expected that more focus on AI-based research will characterize the future of railway engineering, planning and management. Thus, many open research topics are envisioned, some of which could contribute to general usage of AI. Future research can be expected towards developing advanced combined AI applications, using AI in decision making and assisting optimization approaches, dealing with uncertainty and tackling newly rising cyber–physical threats.

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