Deliverable D 5.3

Report on identification of migration strategies and roadmaps for AI integration in the rail sector

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Contents

Executive Summary

This document provides roadmaps for the adoption of AI in the rail sector with a specific focus on autonomous trains, maintenance and inspection and traffic planning and management. More specifically, this document provides a detailed account of the steps taken and the results obtained in the roadmapping process, which was conducted through the research activities of the project. It also includes references to the documents that describe and report on the outcomes achieved. Additionally, it finalizes the roadmapping process by addressing considerations regarding the timeframes necessary for achieving full applicability and maturity of AI-powered solutions stemming from the proof-of-concepts developed in the project, the associated criticalities, and suggestions for future research directions. By addressing specific and overarching aspects, this document aims to drive further development, experimentation, and application of AI, ultimately fostering efficiency, safety, and progress in the railway industry as a whole.

Abbreviations and acronyms

Abbreviations / Acronyms	Description
AI	Artificial Intelligence
AIDT	AI-aided Digital Twin
AoE	ATO over ETCS
ATC	Automatic Train Control
ATO	Automatic Train Operation
ATP	Automatic Train Protection
ATS	Automatic Train Supervision
CI	Cloud Intelligence
DT	Digital Twin
EI	Edge Intelligence
ETCS	European Train Control System
FI	Fog Intelligence
GoA	Grade of Automation
GoI	Grade of Intelligence
HMI	Human-Machine Interface
I2X	Infrastructure-to-Everything
IDK	I Do not Know
IHM	Infrastructure Health Monitoring
IoT	Internet of Things
IT	Information Technology
ITC	Intelligent Train Control
ITO	Intelligent Train Operation
ITP	Intelligent Train Protection
ITS	Intelligent Train Supervision
LoI	Level of Intelligence
PoC	Proof-of-Concept
PT	Physical Twin
RUL	Remaining Useful Life
SIL	Safety Integrity Level
T2X	Train-to-Everything
TRL	Technology Readiness Level
VBODS	Vision-Based Obstacle Detection System
VC	Virtual Coupling
VHM	Vehicle Health Monitoring
WP	Workpackage

1. Background

RAILS is a research and investigation project producing outcomes at TRL levels 2-3. The research was conducted in three phases to:

- **Discover** the potential of AI for railways identify promising application areas in the rail sector and specific needs and related challenges;
- **Assess** the impact of AI techniques by performing an analysis of other relevant sectors, defining pilot case studies and applying selected approaches to the pilot case studies in concrete operational scenarios;
- **Learn** the distance from the current state of the art in railways and the digital and technological prerequisites for AI adoption, the possible innovations, the research directions and impacts for the European rail sector as to provide indications, recommendations and proper guidelines for future research and implementations.

The RAILS project followed the Technology Road-Mapping Methodology in order to suggest strategies for the fast take up of AI technology in railways, therefore the research activities that have been carried out during the project must be seen as part of a single roadmapping process. Figure reffig:rails depicts the logical connections between the three phases and the railway realms addressed by the project.

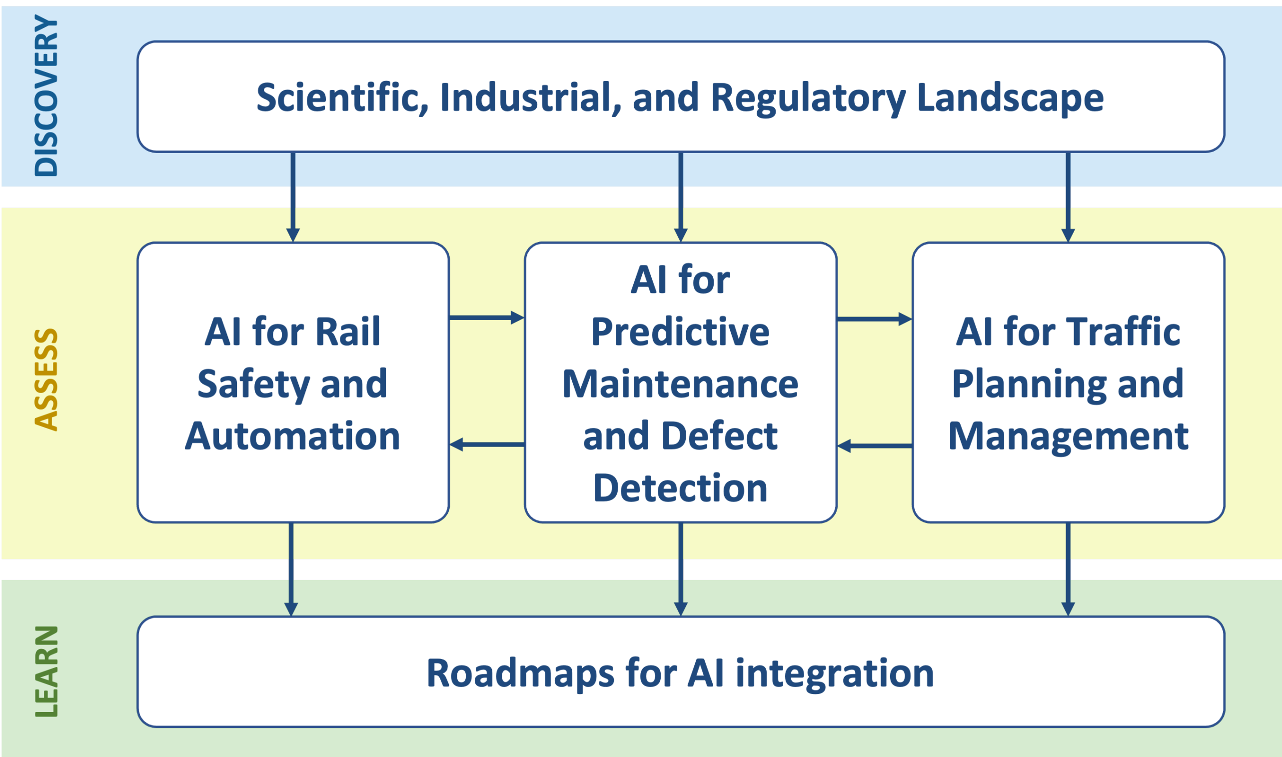

Fig. 1.1. RAILS Phases and Scope

2. Objective

The objective of this document is to outline the RAILS roadmapping process, which is aimed at exploring the integration of Artificial Intelligence (AI) within various aspects of the railway industry and research, with a specific focus on control and autonomous driving, predictive maintenance and defect detection, and traffic planning and management.

Through a comprehensive description of the roadmapping journey, this document aims to provide a clear understanding of the steps undertaken and the outcomes achieved throughout the process. It delves into the specifics of each topic area, examining the estimated maturity levels and timeframes for the adoption of AI technologies.

By presenting the current criticalities and challenges associated with integrating AI in the railway sector, the document seeks to shed light on the issues that need to be overcome for successful implementation. Additionally, this document highlights the emerging directions and opportunities discovered through the roadmapping process, underscoring mixed-reality technologies, dataset sharing for benchmarking AI technologies, and promising future railway applications.

Overall, it serves as a guiding roadmap for effectively harnessing the power of AI to enhance safety, efficiency, and performance within the railway industry.

3. Introduction

The present document reports about the overall RAILS research to shape the roadmaps for the exploitation of AI in railways, including promising research directions and strategies for a safe take-up of AI techniques.

All the activities carried out in the project constitute the implementation of a roadmapping process, as explained in Chapter 4, and therefore, the results obtained effectively form a technological roadmap for research in the field of applying artificial intelligence in the railway sector.

Hence, Chapter 4 presents a comprehensive overview of the roadmapping process, highlighting the key steps taken and the results achieved. It serves as a synthesis of the project's activities and their alignment with the roadmap and explains how the outcomes of these activities can be mapped onto the roadmaps. This involves linking the achieved results to the corresponding milestones and goals outlined in the roadmap process for all the topics addressed by the project.

In the following chapters, the report delves into the specifics of the roadmap for each topic addressed in the project, providing guidance for future research and a timeline for achieving full maturity in the use of AI-based technologies in the specific domain at hand. An online survey was conducted during the final event of the project among a group of experts in the topics and the issues related to the application of AI techniques to railways. The finding from this survey have been included.

Specifically, Chapter 5, 6, and 7 are devoted to the topics covered in the three technical workpackages during the *assess phase* of the project, whereas Chapter 8 explores cross-cutting themes and research areas that have emerged from the project and have relevance across multiple topics addressed in the roadmaps.

4. RAILS Roadmapping Process

4.1. Introduction

Technology roadmapping is a technique to support planning and pursue short-term or long-term goals exploiting specific technology solutions [1]. Technology roadmaps have been classified in the literature according to their purpose and seven types of roadmaps have been identified in [2]: Product planning, Service/capability planning, Strategic planning, Long-range planning, Knowledge asset planning, Program planning, Process planning, and Integration planning.

Although the most common types are Product and Service planning, RAILS specifically focused on the development of roadmaps for strategic planning, supporting the evaluation of strengths, weaknesses, opportunities, and threats of Artificial Intelligence technologies and approaches in the development of the future Railways, by comparing the current status of practice with strategic options explored to bridge the gaps. In this Chapter, the RAILS roadmapping process is illustrated to provide a bird's eye view of the work and main outcomes of the project.

4.2. Roadmapping Steps and Outcomes

Due to the broad scope of the investigation conducted in RAILS, more roadmaps have been developed. The roadmaps are in selected research macro-areas related to or crossing the technical work packages WP2, WP3, and WP4.

The developed roadmaps are intended to provide indications and suggestions for the next research activities in the field:

- They suggest ideas and propose steps to foster innovation in railways;
- They may help reach a consensus about the steps required to bridge the gap between the opportunities opened by AI and the full exploitation of AI solutions;
- They provide recommendations and information to support the innovation process.

The technology roadmapping process includes three phases: preliminary activities, development of the roadmap, and follow-up activities.

The preliminary phase defines the scope and boundaries of the technology roadmap. This phase has been conducted during the preparation of the project proposal when three macro-areas have been selected for the roadmapping and the objectives have been identified as well as during the first phase of the project, through the definition of a taxonomy of AI for railways (WP1).

In the development phase, the following seven steps were taken in RAILS for each macro-area:

1. Identify the railway services/systems/products, i.e., identify the concrete railway problems that are the focus of the roadmaps.
2. Define the critical system requirements on the basis of what is decided that must be road-mapped, e.g. identify applicability issues, constraints, and requirements.
3. Specify the major technology areas, case studies, and operational scenarios.

4. Transform requirements into technology drivers with specific targets according to each operational scenario.
5. Develop AI-powered approaches/solutions and Identify alternatives, where possible, and their timelines.
6. Identify innovation needs and recommended improvements.
7. Create the *Technology Roadmap Report*.

The roadmap development phase was carried out for each macro-area, we recall that the three macro-areas are: Rail Safety and Automation (WP2), Predictive Maintenance and Defect Detection (WP3), Traffic Planning and Management (WP4). The first step for all roadmaps was done in WP1, through a review of the scientific literature, the examination of the ongoing work in European and overseas projects, the analysis of the EU regulation and directives at the date, and a survey among the railway stakeholders on the challenges and the state-of-practice of the usage of AI in railways.

Table 4.1 provides a mapping between the roadmaps development steps and the deliverables in which the related activities and outcomes are reported.

Table 4.1: Roadmapping Steps, Reports, and Outcomes

#	Step	WP2	WP3	WP4	Outcomes
1	Identify concrete railway problems.	D1.1 D1.2	D1.1 D1.2	D1.1 D1.2	Identification of Railway problems and review of AI applications to Railway problems. Identification of research directions and uncharted areas emerged from the analysis of the state-of-the-art.
2	Identify constraints, applicability issues, and requirements.	D1.1 D1.3	D1.1 D1.3	D1.1 D1.3	Review of EU guidelines, Regulations and directives on AI, Explainable AI, Criticalities and milestones, Ethical and Privacy aspects, Urgent issues and strategic application areas.
3	Specify technology areas, pilot case studies, and operational scenarios.	D2.1 D2.2	D3.1 D3.2	D4.1 D4.2	AI Emerging Technologies in sectors other than Railways, Transferability guidelines, Pilot Case studies identification, Scenarios definition.
4	Transform requirements into technology drivers	D1.3 D2.1 D2.2	D1.3 D3.1 D3.2	D1.3 D4.1 D4.2	Basic AI Usage Guidelines, Enabling Technologies, Reference datasets and Machine Learning models
5	Develop AI-powered approaches, Identify alternatives, and their timelines.	D2.3	D3.3	D4.3	Proof-of-concepts (PoCs) for the selected scenarios: KPIs, ML models, Experiments, Results, Possible alternatives
6	Identify innovation needs and recommended improvements.	D2.4	D3.4	D4.4	Results of the SWOT Analysis of the PoCs, Recommendations and Innovation needs
7	Create the Technology Roadmap Report	All the above D5.3	All the above D5.3	All the above D5.3	This document: Timeline indications derived from: i) previous steps ii) relevant stakeholders's opinion, and iii) further available analysis results. Current criticalities and suggested research directions for innovation

As can be seen from the table, the *Technology Roadmap Report* is in all respects distributed among the project deliverables. The present document just tries to summarize the main outcomes and provides a synthesis, also including the time horizon, but it cannot cover all the aspects and results reported in the previous deliverables which all together report the developed roadmaps.

Finally, the third phase of the roadmapping process consists of the follow-up activities. The roadmaps must be disseminated and presented to the railway target groups, so that they can be discussed, validated, and hopefully used with the necessary modifications by the railway stakeholders to stimulate future research and impact the next railways. This would be the best possible exploitation of the project results.

4.3. Summary of Implemented Proof-of-Concepts

The main results from Proof-of-Concepts (PoCs) and general recommendations are reported in deliverables D2.4, D3.4, and D4.4. In this section, a synthetic overview is provided. Please refer to the specific deliverables for an in-depth treatment and discussion.

Following the outcomes of the first phase of the project, two pilot case studies have been identified for each technical WP to investigate innovative and strategic applications of AI methods in different railway domains, and a PoC has been developed for each case study. In addition, general research directions have been investigated.

The pilot case studies (and related PoCs) are the following:

- WP2 - Artificial intelligence for rail safety and automation.
  - “Vision-based Obstacle Detection on Rail Tracks”. The related PoC developed a modular approach with two main objectives: i) to detect any kind of obstacle by leveraging **Unsupervised Deep Learning** for anomaly detection, and ii) to investigate the potentiality and limits of the simplest system mounted on-board the train (i.e., a single RGB camera).
  - “Cooperative Driving for Virtual Coupling of Autonomous Trains”. The related PoC proposed a **Deep Deterministic Policy Gradient** (DDPG) control strategy, which belongs to the Deep Reinforcement Learning (DRL) methods, to investigate the effectiveness of the Virtual Coupling tactical layer.
- WP3 - Artificial intelligence for predictive maintenance and defect detection.
  - “Smart Maintenance at Level Crossings”. The related PoC developed a multi-modular framework for the intelligent monitoring of Level Crossings (LCs) based on **Deep Learning and non-intrusive sensors** (cameras and microphones).
  - “AI-based Rolling Stock Rostering”. The related PoC proposed a rostering/maintenance framework exploiting **Reinforcement Learning**.
- WP4 - Artificial intelligence for traffic planning and management.
  - “Primary Delay Prediction”. The related PoC had the objective to explore and evaluate the effectiveness of delay prediction frameworks using advanced AI algorithms, such as the **Structural Deep Network Embedding** algorithm and **Principle Component Analysis**.
  - “Incident Attribution Analysis”. The related PoC used **Big Data** for interactive delay attribution visualization to reproduce how delays are triggered and subsequently propagated due to small disturbances, disruptions, or unexpected events,

and exploited **Graph Neural Network techniques** for predicting potential propagation links.

For each PoC the roadmapping steps have been carried out and reported as summarised in Table 4.1. Experiments have been conducted and the results obtained have been discussed in Deliverables D2.3, D3.3, and D4.3 respectively.

From the research activities, recommendations and innovation needs have been identified in deliverables D2.4, D3.4, and D4.4 where the results of the SWOT analysis performed for each PoC are also reported. The SWOT analysis is a strategic evaluation model used in various contexts. In RAILS, we applied the SWOT analysis to identify and assess the internal and external factors of the approaches and/or techniques used to develop the PoCs. These factors include: *Strengths*, which are advantageous internal aspects that contribute to success; *Weaknesses*, representing internal limitations that could hinder success; *Opportunities*, external factors that offer the potential for success; and *Threats*, external elements that could pose risks to success.

Figures 4.1, 4.2, and 4.3 provide a consolidated and synthetic overview of the SWOT analysis results that are distributed and discussed across three distinct documents, allowing for a comprehensive view of the main factors impacting the investigated approaches as they emerged from our studies. Therefore, the reported factors just refer to our PoCs implementations and the specific AI techniques we adopted for the PoCs as specified above and in the caption of the figures.

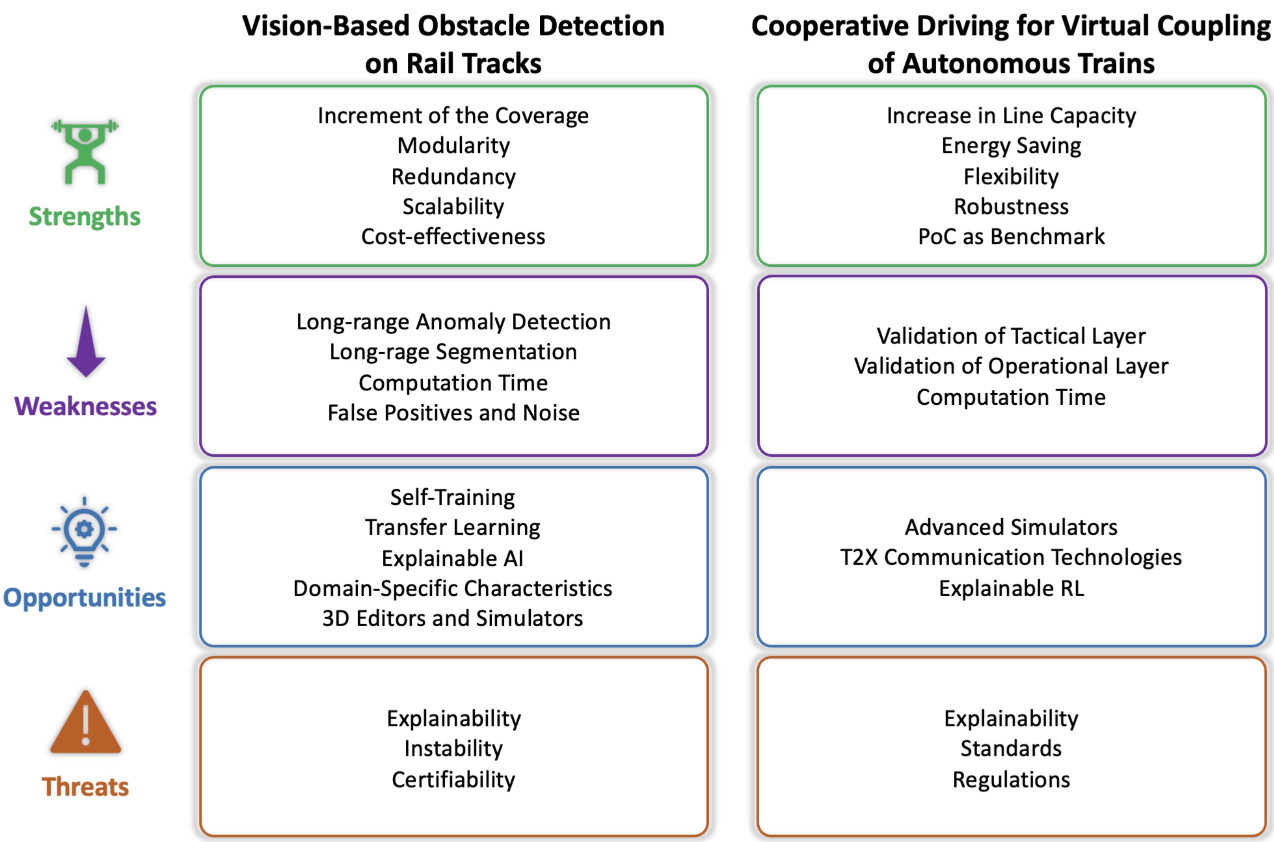

Fig. 4.1. SWOT results for WP2 PoCs - Left: Unsupervised DL for anomaly detection, single RGB camera - Right: DDPG control strategy.

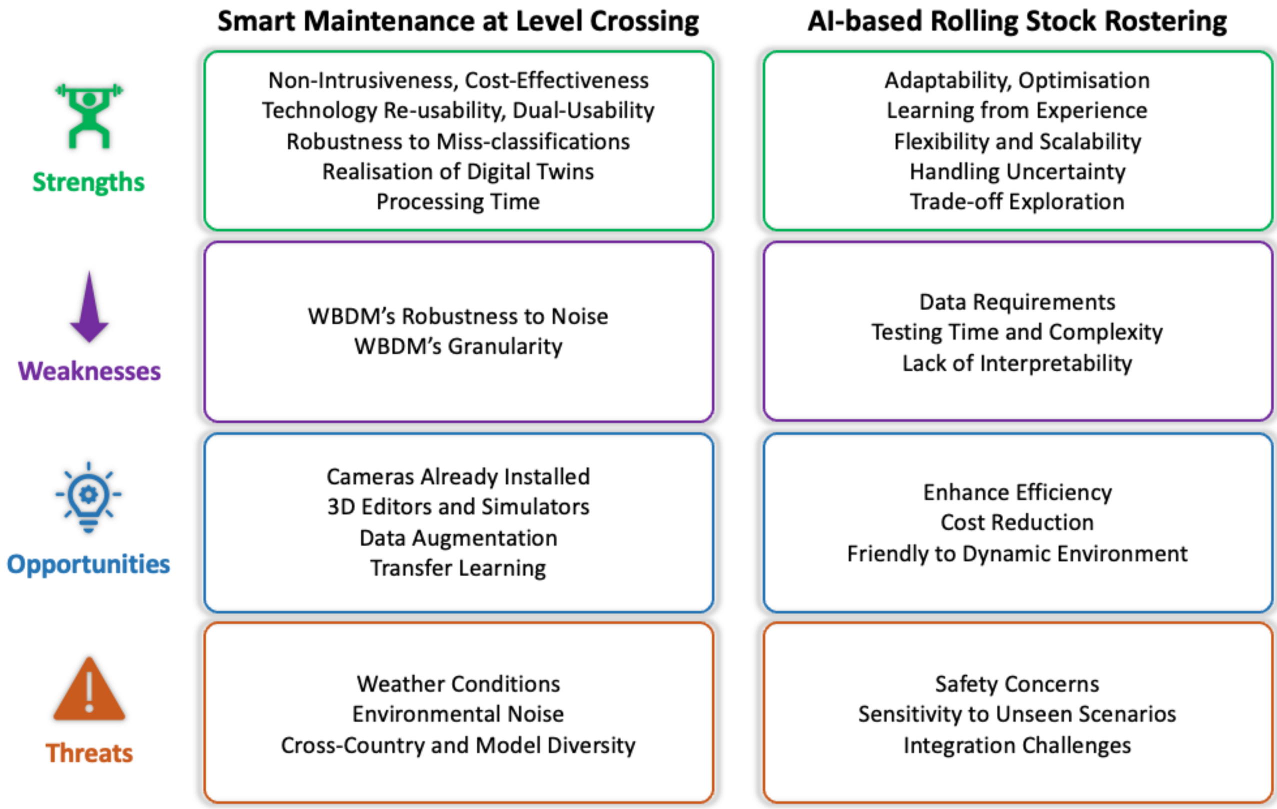

Fig. 4.2. SWOT results for WP3 PoCs - Left: Intelligent monitoring of LCs based on Deep Learning and non-intrusive sensors. Right: Rostering/Maintenance framework based on Reinforcement Learning.

As also emerges from the previous discussion, the pilot case studies were conceived as **benchmarks** for developing PoCs. Some of the data collected to develop the "Vision-based Obstacle Detection on Rail Tracks" PoC [1] and the "Smart Maintenance at Level Crossings" PoC [2] were made publicly available on the Zenodo platform.

Several topics have been analysed and investigated in the context of the PoCs and more in general in the context of the three technical work packages. Such topics were either functional for the research activities or strictly connected with the application area addressed by the case studies. They span from the role and opportunities offered by digital twins to the cloud, edge, and fog computing paradigms, as well as the challenges posed by the lack of appropriate datasets and the necessity for new standards and regulations. These topics were also investigated, and some of them were included in the survey conducted at the project's conclusion. The goal was to engage a group of railway experts in discussing the associated matters and estimating the time needed to achieve complete technological maturity. The outcomes of this survey, along with the research directions that emerged from the comprehensive research and analysis conducted throughout the project, are detailed in the following chapters.

[1] https://zenodo.org/record/7924875
[2] https://zenodo.org/record/7945412

	Primary Delay Prediction	Incident Attribution Analysis
Strengths	Captures Network Topology Non-linear Mapping Scalability and Efficiency Robustness to Noise/Missing Data	Scalability Inclusion of Node Features Inductive Learning Flexibility
Weaknesses	Data Requirements Interpretability	Data Availability and Quality Interpretability
Opportunities	Enhanced Prediction Accuracy Incorporation of Additional Features	Proactive Decision-making Real-time Incident Response Network Optimization
Threats	Generalisation to New Environments Overreliance on Network Structure	Generalisation to Different Contexts Data Scalability

Fig. 4.3. SWOT results for WP4 PoCs - Left: Structural Deep Network Embedding algorithm and Principle Component Analysis. Right: Big Data for interactive delay attribution visualisation and Graph Neural Network techniques for predicting propagation links.

4.4. The Roadmapping Survey

Two surveys were conducted during the project, each with distinct aims and scopes. The first survey aimed to assess the state-of-practice, challenges, and issues related to the adoption of AI in the railway sector. Conducted in the project's initial phase, it aimed to provide valuable insights into the research activities. Railway stakeholders within the RAILS target groups were invited to participate in an online questionnaire, designed to gather comprehensive information.

The second survey took place within an interactive session hosted at the project's final event. The questionnaire was administered to a panel of about 40 experts from industry, academia, and regulatory bodies. The purpose was to gather information necessary for shaping roadmaps regarding the application of AI in the project's focused areas and ensure that the project's insights in these domains were representative of the collective knowledge and expertise within the railway community.

The questionnaire included four sections, one for each work package, and a section related to cross-cutting topics. Within each work package, two topics addressing relevant technology were included as follows:

- *WP2-related topics:*
  - Fully Autonomous Trains in Open Environments.
  - Obstacle Detection Through On-board Cameras and Artificial Vision.

- *WP3-related topics:*
  - Intelligent Audio-Video Technologies for Non-intrusive Infrastructure Inspection.
  - Intelligent Digital Twins for Predictive Maintenance of Railway Assets.
- *WP4-related topics:*
  - Train Delay Prediction using Machine Learning
  - Railway Incident Attribution Analysis Using Big Data Analytics.

The fourth section included the following topics:

- Mixed-Reality Technologies to Support AI Testing
- Sharing Relevant Datasets for Benchmarking AI Technologies for Railways.
- Promising AI Applications to Railways in the Next 10 Years.

For every topic, the same set of question types was employed:

- Technology Readiness Level (TRL) Question: A multiple-choice question asking about the estimated TRL of the technology. For the sake of clarity Table 4.2 provides a correlation between each TRL and its corresponding description.
- Commercial Availability Question: A multiple-choice question inquiring about the expected time for the technology to full maturity.
- Critical Points Question: An open-ended question prompting respondents to identify issues to be overcome.

This structure was consistently applied across all work packages and topics, facilitating a clear and uniform approach to gather information.

Table 4.2: Technology Readiness Level (TRL)

Level	Description
TRL1	Basic principles observed.
TRL2	Technology concept formulated.
TRL3	Experimental proof-of-concept.
TRL4	Technology validated in lab.
TRL5	Technology validated in relevant environment.
TRL6	Technology demonstrated in relevant environment.
TRL7	System prototype demonstration in operational environment.
TRL8	System complete and qualified.
TRL9	Actual system proven in operational environment.

5. Integrating AI in Railway Safety and Automation

5.1. Introduction

Over the last few years, there has been a huge interest in improving the automation, efficiency, and capacity of railway lines, with safety being the central aspect to be ensured in order to provide passengers with reliable services.

So far, railway lines have been classified according to some Grade of Automation (GoA) levels (reported in Table 5.1) which reflect the presence of automatic train systems (summarised in Table 5.2) and the need for human operators (drivers or crew members) whose constant role across the various level (up to GoA3) is to ensure operations' safety. Nowadays, we can affirm that, in certain circumstances, railway lines have reached the GoA4 level, with trains operating completely unattended with high efficiency. This is the case of various metro lines worldwide, which we can define as *segregate environments* as they are protected from external threats by means of physical barriers (e.g., platform screen doors) which should keep all undesired and harmful events outside from rail tracks.

Table 5.1: Grade of Automation (GoA) levels.

Level	Description
GoA 0	Train operations are manually supervised by the driver, no automation.
GoA 1	Train operations are manually supervised by the driver supported by ATP.
GoA 2	Semi-automatic train operation. ATO and ATP systems automatically manage train operations and protection while supervised by the driver.
GoA 3	Driverless train operation with on-board staff handling possible emergencies.
GoA 4	Unattended train operation, neither the driver nor the staff is required.

Table 5.2: Automatic Train Systems.

System	Description
Automatic Train Operation (ATO)	Used to automatically drive the train and stop at stations when needed.
Automatic Train Protection (ATP)	Used to automatically protect the train by applying brakes when needed.
Automatic Train Control (ATC)	Both ATP and ATO are in place to ensure full control of the train.
Automatic Train Supervision (ATS)	Used to manage train schedules and coordinate routes along whole tracks.

Considering the investigations conducted within the RAILS project, things get more complicated when talking about *open environments* (e.g., main railway lines), which may also present interconnections with other domains (e.g., with roads at level crossings). Hence, safety cannot be ensured by using static physical barriers and must be managed at runtime by, for example, giving trains or trackside equipment the capability of analysing multiple factors and taking autonomous decisions in order to both increase efficiency and ensure safety.

Basically, **what** would be needed is a paradigm shift from *Automatic operations* to *Autonomous operations*. *Automation* refers to actions taken automatically or semi-automatically basing on a set of pre-specified rules; differently, *Autonomy* refers to the ability of a system to promptly adapt to any possible situation by taking independent decisions [3,4]. In this context, AI can act as a powerful enabler to autonomy since it can give systems the capabilities of learning from experience and reasoning so that they can autonomously decide which is the best action(s) to be taken; however, there are several concerns that should be faced which are discussed in the following of this chapter.

Within RAILS WP2 we tried to address some aspects related to autonomous trains by facing two specific PoCs: "Vision-based Obstacle Detection on Rail Tracks" and "Cooperative Driving for Virtual Coupling of Autonomous Trains". The first PoC was oriented at understanding to what extent it would be possible to exploit cameras and AI to detect any kind of obstacles on rail tracks; while the second was oriented at investigating how it would be possible to make trains capable of autonomously adapting to the behaviour of a leading train in order to reduce the distance between running trains and consequently improve line capacity and efficiency.

The findings and considerations coming from the aforementioned PoCs, together with the answers to the Roadmapping Survey introduced in the previous sections, converged into the analysis of the topics discussed in the following of this chapter. To be specific, Sections 5.2 and 5.3 summarise and discuss the results of the Roadmapping Survey, analysing the answers related to the topics concerning Railway Safety and Automation, i.e., "Fully Autonomous Trains in Open Environments" and "Obstacle Detection Through On-board Cameras and Artificial Vision". Then, Section 5.4 highlights the needs and the steps that should be considered in order to safely move towards AI-aided autonomous trains by taking into account the survey's results and the findings obtained throughout the whole RAILS project.

5.2. Fully Autonomous Trains in Open Environments

As introduced above, GoA4 has been already reached in segregated environments. Differently, the path towards the actual implementation of **fully automation** and **fully autonomy** seems yet to be completed in open environments.

Up to date, steps have already been taken, also within the Shift2Rail programme (e.g., within X2RAIL-4 [5]), towards the **automation** of open railway environments, with ATO functionalities being introduced in main lines while supervised by the European Train Control System (ETCS) which manages all the safety aspects (e.g., ensures that the speed profile is respected, actuates the emergency brakes, and so on) [6]. This is named ATO over ETCS (AoE) and, interestingly, has already been tested and prototyped in Europe. Also, there have been carried out tests evidencing that ETCS (which is a core component for the AoE) may also be bypassed somehow to apply ATO even on non-ETCS railway lines [6]. As far as we understood, such technologies, which we refer to as AoE for simplicity, currently allow for upgrading main lines up to GoA2. Basically, in AoE GoA2 lines, *rule-based safety*[1] would be ensured by the ETCS (or other protection systems), while the *managed safety*[2] would be ensured by the driver who will oversee the functioning of the automatic systems. Worth underlining, investigations have already started towards the definition of specifics and the delineation of suitable actions to be taken in order to further extend automation functionalities in main lines up to AoE GoA 3/4 [5, 8].

[1] Achieved leveraging rules, formalisms, and protection measures aiming at defining anticipated responses to foreseeable situations [7]

[2] Aiming at avoiding or mitigating non-predictable hazardous events [7]

Within the RAILS project, we tried to understand the role that AI could have in the transition from automatic to autonomous train operation and protection (which visionary could also ensure managed safety without the intervention of human operators). Then, through the Rodmapping Survey, we asked several railway experts to provide us with their vision of the current level of maturity of Fully Autonomous Trains in Open Environments, when they expect to have fully autonomous trains operating on railway lines, and which are the main criticalities/obstacles that must be addressed to achieve full maturity. The results are discussed below.

5.2.1. Estimated Maturity Level and Time to Full Maturity

Figures 5.1 and 5.2 respectively report the distribution of the answers the participants gave to the questions: considering the topic “Fully Autonomous Trains in Open Environments”, i) *“How do you estimate the current Technology Readiness Level (TRL)?”* and ii) *“When do you expect the technology to be commercially available (TRL 9)?”*. In the figures, IDK stands for “I don’t know”.

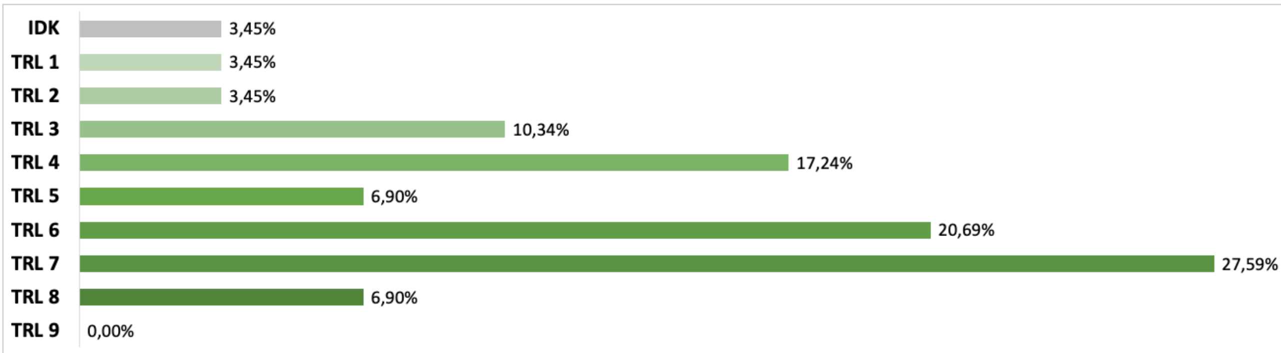

Fig. 5.1. Fully Autonomous Trains in Open Environments: Estimated Maturity Level

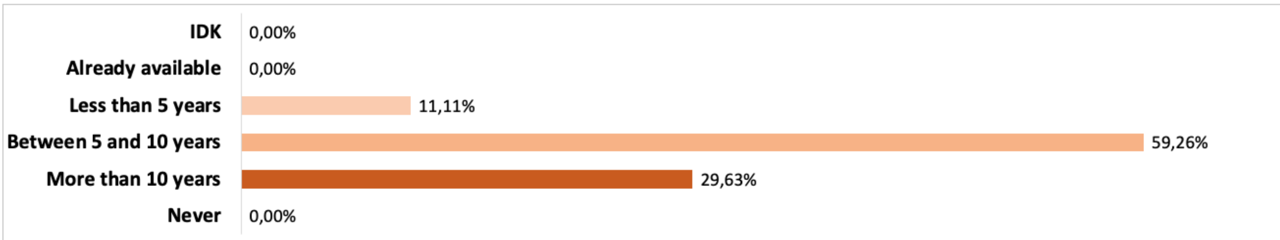

Fig. 5.2. Fully Autonomous Trains in Open Environments: Expected Time to Full Maturity

As for the current maturity level, answers tend towards TRL6/7 indicating that these technologies have been already demonstrated in relevant environments and some working prototypes are already available. The estimated time to full maturity, i.e., that would be needed to complete the systems, qualify them, and prove them in operational environments, is mainly expected to be between 5 and 10 years or beyond.

Interestingly, this prediction seems to be more or less in line with the hype cycles Gartner realised in 2022 for “Transportation and Smart Mobility” (as reported by Thales[3]) and for “Ar-

[3] https://www.thalesgroup.com/en/markets/digital-identity-and-security/government/documents/gartner-hype-cycle-transportation-smart-mobility

tificial Intelligence" [9]. *Autonomous Vehicles* – which, in our view, may include both road vehicles and rolling stock as they could share some AI technologies even if implemented differently – are going through the "Trough of Disillusionment" phase that is explained by Gartner as follows: *"Interest wanes as experiments and implementations fail to deliver. Producers of the technology shake out or fail. Investments continue only if the surviving providers improve their products to the satisfaction of early adopters"*[4]. These technologies, although potentially being game-changers for the transport sector, will require at least another 10 years of evolution before they can actually be implemented in the field.

5.2.2. Current Criticalities

To support the answers in Figures 5.1 and 5.2, participants were also asked to *"indicate the main criticalities that should be overcome"* in order to move towards "Fully Autonomous Trains in Open Environments".

Plenty of different challenges were underlined, which can be clustered as follows:

- **Safety Concerns.** These include the necessity of: i) evaluating the *trustworthiness of AI systems* (especially in safety-critical environments); ii) establishing mechanisms to *prove the safety* of AI systems; and iii) understanding how AI systems could be *verified and validated*.
- **Regulations, Normative, and Legal Issues.** This point is actually linked with the previous one as one of the main aspects in this context is the need of *procedures for the certification* of AI systems to *prove their correctness*. This problem is further exacerbated by the complexity of defining a suitable *test coverage* for AI systems.
- **Social Acceptance.** Users may not trust autonomous trains at this specific level of development.
- **Operability Issues.** These includes, among others: i) *interactions among vehicles*; ii) *the costs of the infrastructures*; iii) *the security of IT systems*; iv) *operational constraints*; v) *long-range obstacle detection* especially with *harsh weather conditions*; vi) *availability, reliability, and security of communications*; and vii) *real-time hazards estimation*.

To summarise, what principal emerged from the survey is that:

- On the one hand, there are some operational constraints that should be met and that, given the current status of development of AI system, still represent open challenges that should be overcome before considering AI systems viable in operational environments.
- On the other hand, new standards and certification processes allowing for the evaluation and certification of AI systems, and thus for the identification of their level of reliability and safety, should be formally developed.

To conclude, a direction that has been highlighted within the survey and that can be taken to overcome the aforementioned issues would be to focus on automotive derived solutions to accelerate the integration of AI-based applications for enhancing safety and automation; i.e., look into automotive to understand whether transferable solutions exist as we did in [10]. Indeed, the automotive field has already identified future research directions to deal with the explainability, ethical, and regulatory challenges related to the diffusion of AI solutions in autonomous vehicles [11].

[4] https://www.gartner.com/en/research/methodologies/gartner-hype-cycle

5.3. Obstacle Detection Through On-board Cameras and Artificial Vision

As better discussed in Section 5.4, one of the main aspects that must to be considered when passing from automatic to autonomous operations is related to the ability of trains of understanding what is happening within the surrounding environment. Giving trains the capability of, among others, detecting obstacles and taking autonomous decisions on what they should do in order to avoid or mitigate possible collisions is an extremely important aspect that falls under the concept of managed safety discussed in Section 5.2 and would be essential to allow trains moving without human supervision.

Obstacle detection systems typically involve multiple sensors (e.g., [12]) and exploit sensor fusion and diversity in order to ensure, to some extent, reliability in case one or more sensors (and related systems) would fail in detecting the obstacles. In the context of the RAILS project, however, we focused on a specific subsystem involving the usage of on-board cameras only, namely Vision-Based Obstacle Detection System (VBODS), which may visionary be used as a stand-alone system to support autonomous operations in specific and constrained cases while being cheaper than the whole complex system introduced above.

We asked several railway experts to provide us with their vision of the current level of maturity of VBODSs, when they expect to have fully autonomous trains operating on railway lines, and which are the main criticalities/obstacles that must be addressed to achieve full maturity. The results are discussed below.

5.3.1. Estimated Maturity Level and Time to Full Maturity

Figures 5.3 and 5.4 respectively report the distribution of the answers the participants gave to the questions: considering the topic "Obstacle Detection Through On-board Cameras and Artificial Vision", i) *"How do you estimate the current TRL?"* and ii) *"When do you expect the technology to be commercially available (TRL 9)?"*

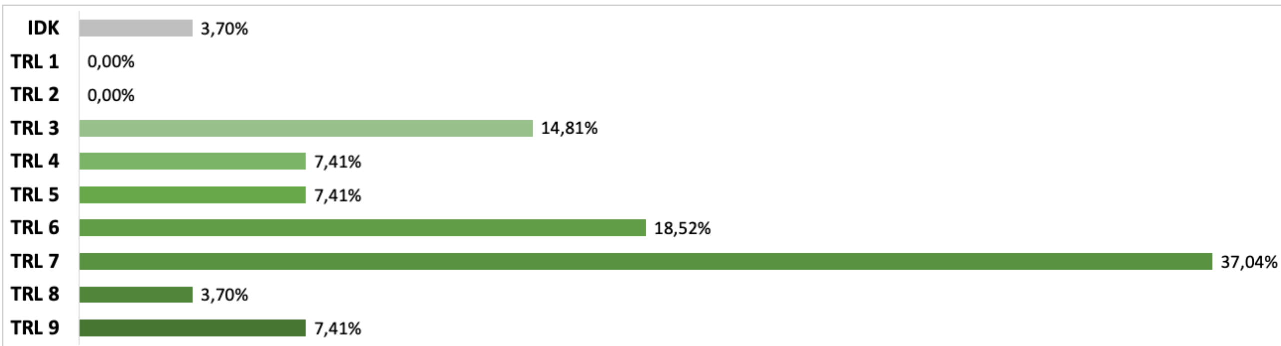

Fig. 5.3. Obstacle Detection Through On-board Cameras and Artificial Vision: Estimated Maturity Level

The most voted option is TRL 7, while the technology is expected to be fully mature in less than 5 years. Interestingly, there may be evidence of VBODSs which are already at TRL9 and are already available to be used.

This is also in line with the prevision that Gartner made last year for Computer Vision (CV) applications in the context of AI [9], indicating that these approaches are now within the "Slope of Enlightenment" phase and are about to reach the "Plateau of Productivity" in less than two years (one year from now). Clearly, CV encompasses a plethora of techniques, and

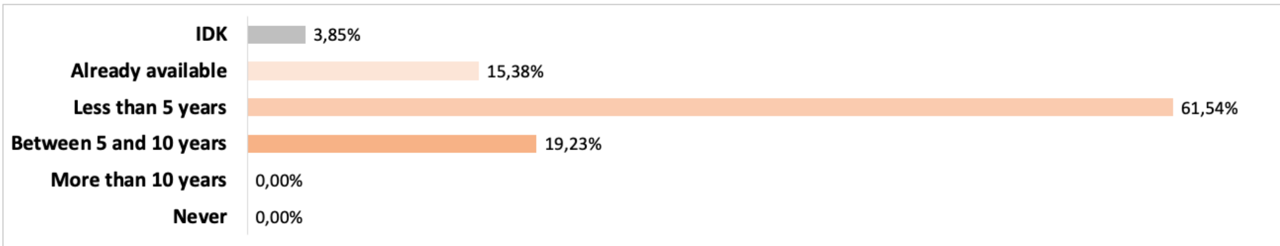

Fig. 5.4. Obstacle Detection Through On-board Cameras and Artificial Vision: Expected Time to Full Maturity

Vision-Based Obstacle Detection may exploit only a subset of them (e.g., object detection, semantic segmentation, and so on). Therefore, with a specific focus on VBODSs, it would be necessary to understand if these techniques will effectively reach an adequate level of maturity in the following few years to be used in safety-critical environments such as railways. Knowing that, we asked the participants to the survey to indicate which, according to their experience, are the main issues that must be considered (or that have been already faced for TRL9 VBODSs) in order to make VBODSs suitable and reliable for railway environments; the results are reported below.

5.3.2. Current Criticalities

As for the wider topic of "Fully Autonomous Trains in Open Environments", concerns were expressed for the *Certifiability and Standardization* of these systems, together with the difficulties of achieving a suitable *Test Coverage* proving that these systems may be *reliable* in almost all possible conditions. These and the other, more technical, criticalities that were identified can be clustered as follows:

- **Reliability Concerns.** It seems not to be trivial, at the current level of development, to understand to what extent these systems can be considered reliable. In this direction, Explainable AI could help to better understand the reasoning of AI systems, but it should be further developed.
- **Implementability Issues.** These include *sensors costs* and the need for *energy-efficient AI models*, but also the problems of *data availability*, *data completeness*, and *appropriate data annotation*.
- **Performability Issues.** These encompass, among others, the *small-scale object detection problem*, *detection distance*, and *the robustness of these systems to false alarms*.
- **Operability Issues.** These involve all the problems arising from the operational environment, such as *harsh weather conditions* that could *limit the visibility* of VBODSs and the *diversity of the nature of the obstacles* which make their behaviour and dynamic movement difficult to understand and predict. Also, to effectively implement obstacle detection in complex railway networks, it would be required to *know the route of the train upstream the turnouts (or switches).*

In addition to these criticalities, other comments were made on the usage of on-board camera sensors:

- Camera sensors are the most affected by harsh environmental and low light conditions.

- Given trains' speed (especially in high-speed railways) and the resulting braking distance needed to safely stop them, on-board cameras may not be sufficient to detect obstacles well in advance.
- It is needed to know the exact distance of the obstacles from the train at each instant in time; which is an extremely complex task to solve if only cameras are used.

Possible solutions to these problems regard the integration of on-board cameras with other sensors (like LiDARs, radars, and so on) installed both on-board and on trackside infrastructures to better monitor railway lines even beyond "train's visibility". Sensor fusion introduces diversity, potentially making the system more reliable. However, also in this case, as highlighted by the participants to the survey, there are still challenges to overcome including: i) *adequate and multiple validation methods* to effectively evaluate obstacle detection systems against reference standards; ii) *sensors latency and calibration* which could compromise the detection (possibly, *edge computing solutions* could be adopted to reduce latency); and iii) *processing speed* from the data acquisition to the obstacle detection.

To conclude, it has also been highlighted that *AI may not be the unique solution*. AI may help to implement mechanisms oriented at detecting the dynamic of the obstacles and possibly to dynamically adapt to changes in the environment, however, data analysis can also be done by means of traditional techniques (e.g., image processing not based on AI) which could be more reliable and understandable. Therefore, AI would be only part of the solution and not *the* solution; both AI and traditional approaches would be required in order to achieve effective obstacle detection systems.

5.4. Future Research Directions

At the beginning of this chapter, we introduced **what** would be required to move towards autonomous trains in open environments; i.e., a paradigm shift from *Automatic* to *Autonomous* systems.

In this section, we try to underline **how** this paradigm shift could be supported and **which** would be, among others, the enabling factors and technologies that should be further investigated for the **effective introduction of AI-aided Autonomous Trains in Open Environments**. This is done on the basis of:

- The findings obtained while analysing the state-of-the-art (RAILS WP1 Deliverables and Deliverable D2.1).
- The expertise acquired while working on the RAILS WP2 PoCs (Deliverables D2.2 and D2.3).
- The recommendations identified in Deliverable D2.4.
- The results of the Roadmapping Survey.

Conceptual Shift. Current GoA levels, which indicate the presence/absence of automatic functionalities, do not allow for the correct classification of railway lines characterised by AI-powered autonomous behaviours. A new classification would be required to:

- Extend and support GoA levels.
- Drive the step-by-step introduction of AI-aided autonomous functionalities in railway lines.

To that aim, in Deliverable D2.4 and [4], we established some Grades of Intelligence (GoI) which were built upon GoA levels to extend their coverage in order to guide, somehow, the step-by-step integration of AI in railway lines.

Before proceeding, it is important to underline that GoIs should be considered as examples, as suggestions on how AI could be introduced step-by-step into safety-critical railway systems; they should not be intended as a new standardised classification of railway lines. Also, GoIs, as were conceived within the RAILS project, are **not intended** to replace GoA levels; instead, GoIs are built alongside GoAs with the only intent of trying to classify AI integration in autonomous railways functionalities.

In this section, we re-propose the GoI classification introduced in our previous WP2 deliverables by extending their description and providing indications on the steps that should be performed to gradually introduce AI for autonomous trains from **limited/no autonomy** (GoI1) to **full autonomy** (GoI3/4). GoIs also provide an increasing level of difficulty for the integration of AI functionalities, given the safety-critical nature of some functionalities and the need for advanced information and management systems. From this perspective, GoI levels (shown in Fig. 5.5) can be summarised as:

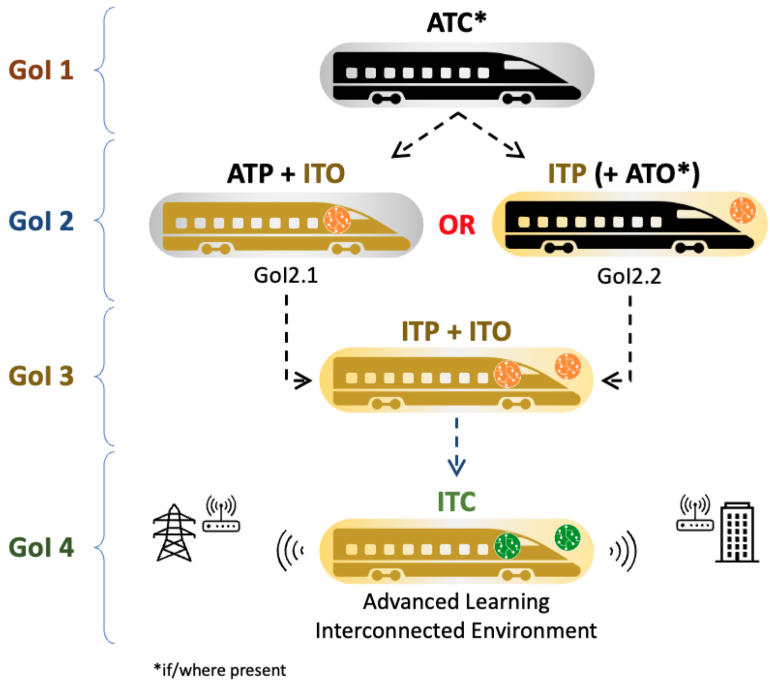

Fig. 5.5. GoI Levels.

- **GoI1 - Limited/No Autonomy**: AI is not introduced in any safety-critical train driving functionality. Instead, AI can be adopted as a tool to optimise or support ATS functionalities (e.g., optimise train scheduling) introducing a conceptual shift from Automatic to Intelligent Train Supervision (ITS).
- **GoI2 - Partial Autonomy**: AI is used to improve ATO functionalities (GoI2.1) or, *alternatively,* ATP functionalities (GoI2.2). Hence, GoI2.1 and GoI2.2 are in *mutual exclusion* and represent two different modalities through which partial autonomy can be achieved:

- **GoI2.1:** AI is introduced to extend ATO functionalities by applying intelligent and adaptive behaviour in order to optimise passenger comfort, energy consumption, and line capacity. AI-powered ATO is referred to as Intelligent Train Operation (ITO). In this specific case, protection systems (e.g., ATP or equivalent) are *necessary* to monitor ITO actions and apply protection if needed.
- **GoI2.2:** AI-aided ATP, i.e., Intelligent Train Protection (ITP), supports, extends, or potentially replaces traditional ATP. If the ATP is not available (e.g., in old railway lines or when ATP failures oblige to partial supervision), ITP could replace ATP by, e.g., automatically recognising signals and/or obstacles. If ATP is available, ITP can be a useful complement to detect events that are not managed by ATP.

GoI2.2 is way more challenging to achieve than GoI2.1 especially given safety, certifiability, and reliability concerns as pointed out in Sections 5.2.2 and 5.3.2. Basically, ITP adopts AI to *directly* manage safety aspects. Therefore, this must be certified as SIL4; however, to the best of our knowledge, this seems not to be possible at this level of development of AI technologies.

- **GoI3 - Full Autonomy**: both ITO and ITP are implemented to allow trains to operate in full autonomy. However, at this level, no advanced learning and adaptation capabilities are considered (e.g., online learning). For instance, ITP's artificial vision systems can be trained only once, e.g., to detect on-track obstacles, and never updated in real-time.
- **GoI4 - Full Autonomy in Fully Connected Environments**: as GoI3, both ITO and ITP are implemented, but they would be also required:
  - Advanced learning and adaptive capabilities to constantly learn in real-time how operations can be further optimised.
  - A fully-connected and dynamically updated ecosystem with extremely reliable connections so that trains can be constantly updated with information related to safety and operability aspects also coming from other assets on the same railway track (e.g., other trains, level crossings, stations).
  - Advanced analysis mechanisms giving trains the capability of predicting the health status of their on-board components so that driving decisions can be taken by also considering what would happen to on-board components if a specific action would be taken.

  The latter aspect – typically referred to as Vehicle Health Monitoring (VHM), Intelligent VHM in this case – is something that can be achieved also at lower GoIs; however, it is particularly required at this level as it, together with ITP, could give trains all the relevant information to *consciously* take safer actions.

  From this perspective, GoI4 should be supported by higher levels of fog/cloud intelligence (introduced afterwards) by using external AI models for big data analytics, such as those enabled by Digital Twins.

Basically, the introduction of AI, as it is happening as far as we know, should proceed gradually starting from non-safety-critical functionalities or from those which are not required to be SIL4. In the latter cases, the concept of **safety envelope** [13–15] can be exploited to wrap AI functionalities with railway systems that are already certified as SIL4 in a sort of system-over-the-loop paradigm.

As happens with ATO over ETCS, where the ETCS manages all the safety aspects of the automatic train and supervises the actions taken by the ATO, the same principle can be applied to ITO systems. The ITO, at GoI2.1, would introduce AI to, for example, improve line capacity or energy efficiency while the ATP (which can be rated as SIL4) manages all the safety aspects. The same would go for ITS and, for example, the interlocking system. For further details on the concept of ATP as a safety envelope refer to Deliverable D2.4 and [4].

Structural Needs. In order to efficiently integrate AI systems in railways and exploit their maximum potential, we think that it would be necessary to arrange them according to a specific structure categorising the field of action and the assets/functionalities the AI systems should focus on. We formalised this by introducing, in Deliverable D2.4, some Levels of Intelligence (LoIs) which were drafted upon the concepts of Edge, Fog, and Cloud Computing; for the sake of simplicity, these LoIs are recalled in Table 5.3.

Table 5.3: Levels of Intelligence

Level of Intelligence	Description
Edge Intelligence (EI)	AI systems mounted on-board the assets (e.g., trains) would be in charge of implementing local autonomy (e.g., on-board obstacle detection). They may be characterised by possible limitations in terms of computing power, due to constrained devices, but they would also be advantaged in terms of response times and data security, due to shorter communication links.
Fog Intelligence (FI)	AI systems at this level would monitor a cluster of assets and manage their interconnections in order to achieve a comprehensive optimisation of a railway sub-system. For example, fog intelligence may represent trackside control where capacity optimisation (e.g., Virtual Coupling) can be orchestrated based on a larger knowledge of what is happening within a whole railway line.
Cloud Intelligence (CI)	AI systems deployed at this level would aim at elaborating big amount of data, possibly coming from multiple assets installed worldwide, in order to collect information and knowledge to be either shared with the AI systems operating at lower LoIs or exploited to implement more comprehensive systems. For example, a failure prediction system can be trained with data coming from multiple installations of the same asset. These would most likely include more information about potential failures compared to data obtained by monitoring a single asset only.

These levels would then act as guidelines to set up suitable architectures for AI-aided Autonomous Trains. Inspired by the analysis of the State-of-the-Art and solutions developed within the Automotive sector (analysed in the first phase of the project - WP1 - and in Deliverable D2.1), we tried to formalise an *example* architecture (Fig. 5.6) containing the modules that, in our view, would be required at GoI4. The example architecture shows the modules that would be required from the perspective of AI-powered autonomous trains. Certainly, other modules could be introduced to properly manage an entire railway network where all assets would, visionary, behave autonomously. In addition, at lower GoIs, other modules/systems would be required, e.g., the ATP at GoI2.1.

The layers and components in Fig. 5.6 are discussed herein:

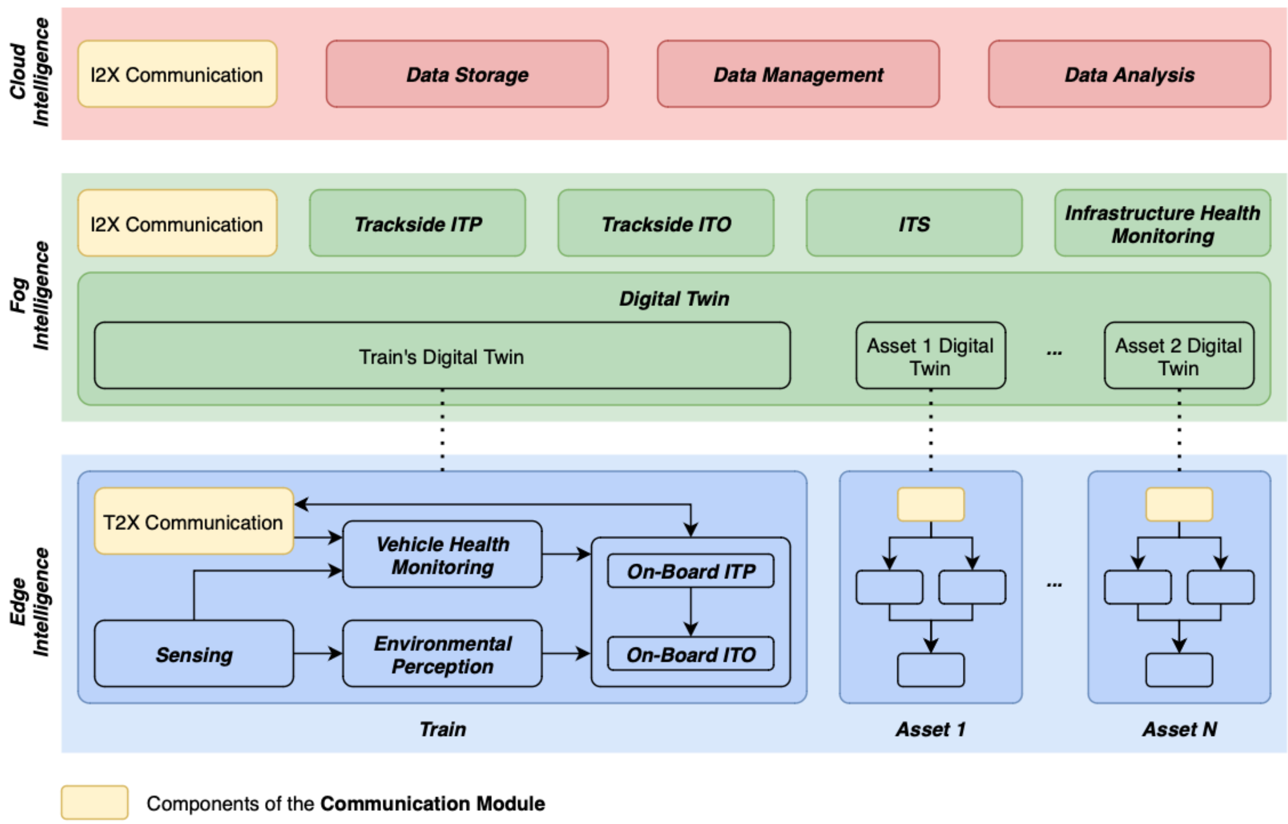

Fig. 5.6. An Example Architecture Towards GoI4 Railway Lines

- **Communication Module**: This module is transverse with respect to the LoIs. In Fig. 5.6, the various components of this module are explicitly indicated at the Edge, Fog, and Cloud Intelligent Levels. Notably, any device would have a communication component. T2X and I2X respectively stand for Train-to-Everything and Infrastructure-to-Everything communication. Communication between railway assets would be critical for the implementation of AI-powered autonomous driving functionalities. For example, Virtual Coupling (as analysed in Deliverables D2.3 and D2.4) requires trains to constantly and reliably communicate with both other trains and trackside infrastructures to establish the optimal driving policy. Disruptions or delays in communication would potentially lead to unpleasant consequences given the reduced distance between trains.
- **Cloud Intelligence:** Modules at this level would be oriented at storing, managing, and analysing data coming from multiple instances installed/operating over multiple railway networks:
  - **I2X Communication**: This component would allow other modules at the CI level to communicate with the modules at lower levels. We marked it as I2X, i.e., CI modules could potentially communicate with FI modules but also directly with EI modules installed in physical entities like trains or other assets. However, further and more in-depth analysis should be made to understand if it would be efficient or counterproductive to let CI modules capable of directly communicating with EI modules bypassing, de facto, the FI level. A trivial example is the following one. Within the *Data Analysis* (discussed below), a specific AI system – which is in

charge of predicting anomalies for component X of a train – has been optimised based on data coming from the same component installed on hundreds of trains. Hence, the system deployed at the EI level which is in charge of monitoring that component must be updated. Whether the update should be done by directly passing information from the CI to the EI level or by passing the information first at the FI and then at the EI level is beyond the scope of this deliverable. This is just to provide an example architecture to show the components (and their role) needed to move towards GoI4.

  - **Data Storage**: persistently store data and information passed by the *Data Management*.
  - **Data Management**: the functionalities of this module are oriented, but not limited, to: i) receiving data from FI (and, maybe, EI) modules and passing them to the Data Storage; ii) elaborating data to make them homogeneous (if needed); iii) collecting the results from the *Data Analysis*; iv) passing relevant information/updates to modules at lower levels. Basically, its role is to pre-process data (if needed) and sort data among modules at lower levels, *Data Storage*, and *Data Analysis*.
  - **Data Analysis**: this is the core module of the CI level. Basically, within this module, there would be all the components oriented at training, testing, and updating AI systems. By leveraging data from the *Data Storage*, AI systems at this level would be trained on data coming from hundreds of instances installed over multiple railway networks. In this way, AI systems like anomaly detectors would probably be more efficient as they have more information from which to extract knowledge. Otherwise, for example at the EI level, systems should be updated by taking into account information coming from a single (or a few) components only which would not be so efficient, especially because it would be required a long time before a sufficient amount of data would be collected.

- **Fog Intelligence:** Modules at this level would be oriented at managing all the assets composing a specific track (or, more in general, a specific railway network). Therefore, it would be possible to have multiple parallel FI Levels under a unique CI Level. Layers/components at the FI Level that would be required for Autonomous Trains are:
  - **I2X Communication**: As for CI, this component manages the communication between FI modules and CI-EI modules.
  - **Trackside ITP**: this module would adopt AI to manage protection considering data coming from multiple assets and traditional protection systems (e.g., ATP). For example, if a train is approaching a level crossing that could potentially be defective, the ITP would then decide whether the velocity of the train must be adjusted to ensure safety.
  - **Trackside ITO**: ITO at the FI level would manage all the information required by the various trains on a specific track to move autonomously. Taking as an example the Virtual Coupling PoC (discussed, in detail, in Deliverables D2.2 and D2.3), ITO would compute in real-time the desired trajectory that each train should follow in order to allow Virtual Coupling. Hence, the desired trajectory is computed at this level and sent to the On-Board ITO (discussed below) of each train which should actuate the driving policy.
  - **Intelligent Train Supervision (ITS)**: this would extend ATS functionalities by ex-

ploiting AI to efficiently optimise (or maximise) railway line utilisation and average throughput by providing appropriate train routing solutions (e.g., promptly responding to disruptions, optimising scheduling/rescheduling, and so on).

  - **Infrastructure Health Monitoring (IHM)**: this module would manage all predictive maintenance aspects that are crucial for the safe running of autonomous trains. The components of this module would monitor all the assets deployed on the rail track in order to predict possible malfunctions that could compromise safe operability.
  - **Digital Twin**: each asset of the rail track would be managed through the corresponding Digital Twin (DT) which is managed by this module. Then, all the modules discussed above, in addition to direct communications with physical assets could also leverage DTs to analyse the status of the assets (without interfering with them) to take decisions that would optimise operations and, at the same time, increase the level of safety. For example, assuming it would be possible to generate DTs for both trains and level crossings, these can be exploited at the FI to promptly adopt countermeasures in case of assets' failure. Additional details are given in Deliverables D3.4 and D4.4.

- **Edge Intelligence**: In Fig. 5.6, as mentioned above, we mainly focused on an architecture including modules that would be essential – to the best of our knowledge – to make trains capable of operating autonomously. Assets 1 to N would either be other trains or railway assets like intelligent level crossings; also, in the case of other types of assets, they could include other components/modules which are not discussed below. The principal modules that a *train* should include are:
  - **T2X Communication**: this component, as discussed for the others at the FI and CI levels, is required to transmit/receive information to/from other trains, assets, or FI modules.
  - **Sensing**: this module would manage all the sensors on-board the train (e.g., cameras, LiDARs, IoT sensors of on-board components, etc.) and apply preprocessing when required.
  - **Vehicle Health Monitoring**: implements mechanisms that give trains the capability of self-analysing the health status of on-board components (i.e., predict failures, detect anomalies).
  - **Environmental Perception**: implements mechanisms that give trains the capability of autonomously analysing the surroundings (e.g., obstacle detection).
  - **On-Board ITP**: exploits data coming from *Vehicle Health Monitoring*, *Environmental Perception*, and FI modules to check whether and which protection mechanisms should be applied (e.g., apply emergency brakes if an obstacle is detected, adjust speed if an onboard component is about to fail, etc.).
  - **On-Board ITO**: exploits data coming from other entities at the EI level (other trains, assets) and other modules at both the EI and FI levels to decide the optimal driving action to take.

Towards Full Autonomy. As also mentioned above, the road towards GoI4 should be travelled step-by-step. The modules in Fig. 5.6 are those that would be necessary to create a fully-connected environment to let autonomous trains (or assets) receive all the relevant information to properly decide the best action to take at a given instant without affecting safety; however, not all of them are required at lower GoIs. Fig. 5.7 shows the modules that would be required for each GoI level. Important to underline, *Automatic Train Systems (Table 5.2) are not bypassed*: for example, given the current level of development of AI systems, ATP would be extremely crucial especially at GoI2.1 to manage possible failures of the ITO. Therefore, the Automatic Train Systems should be considered as potentially mandatory at each GoI with very few exceptions, e.g., in secondary railway lines which are not equipped with ATP but could be equipped with some ITP functionalities (e.g., obstacle detection) to visionary improve safety when these technologies would be mature enough.

As shown in Fig. 5.7:

- At **GoI1**: none of the modules of the example architecture are strictly required but for the communication module which is crucial at any GoI. Any Automatic Train System (ATP, ATO, ATS) can be implemented, indeed, we can have GoA4-GoI1 metro lines. However, GoI1 is characterised by the complete absence of ITP and ITO.
- At **GoI2.1** ITO (both on-board and trackside) is implemented, but ITP is absent. Hence, all the modules that would allow ITO to properly operate or to be further optimised should be installed. Starting from *traditional systems*, ATP is a must as it should be used as the Safety Envelope for the ITO to ensure safety. As an example, the ITO could implement a functionality based on AI to intelligently compute the optimal train speed to save energy and ensure passenger comfort; in case the computed speed would exceed the braking curve computed by the ATP, this would take the proper action to protect the network.
- At **GoI2.2** ITP (both on-board and trackside) is implemented, but ITO is absent. All the modules that would support ITP operations are required. For example, the Environmental Perception module is required because it would implement operations such as vision-based obstacle detection/signal recognition or any other functionality oriented at monitoring the environment looking for potential hazards. These are crucial functionalities for On-Board ITP. The main challenge here is represented by the certification of AI systems that should be rated SIL4 before being introduced in operational environments.
- At **GoI3**: both ITP and ITO are present, together with all the systems that are required to make their interaction possible. This would open for advanced functionalities like Virtual Coupling which has been deeply discussed in Deliverables D2.2, D2.3, and D2.4. Basically, one of the main threats to Virtual Coupling is the certifiability of AI systems that, at GoI3, is supposed to be overcome. In addition, besides the functionalities that Virtual Coupling implements (e.g., computation of an optimal speed profile by leveraging the current speed and position of each train to account for relative braking distances). At this level, Virtual Coupling could also benefit from valuable alternatives, e.g., computing the distance between trains basing on cameras, lidars, and other sensors which, as said, belong to the ITP.
- At **GoI4**: all modules indicated in Fig. 5.6 should be present, including, Vehicle/Infrastructure Health monitoring (VHM, IHM), advanced Data Analysis capabilities at the CI level, and Digital Twins. The role of all these modules has already been discussed above in this document.

Important to mention, there are some modules that are not required at specific GoIs but that

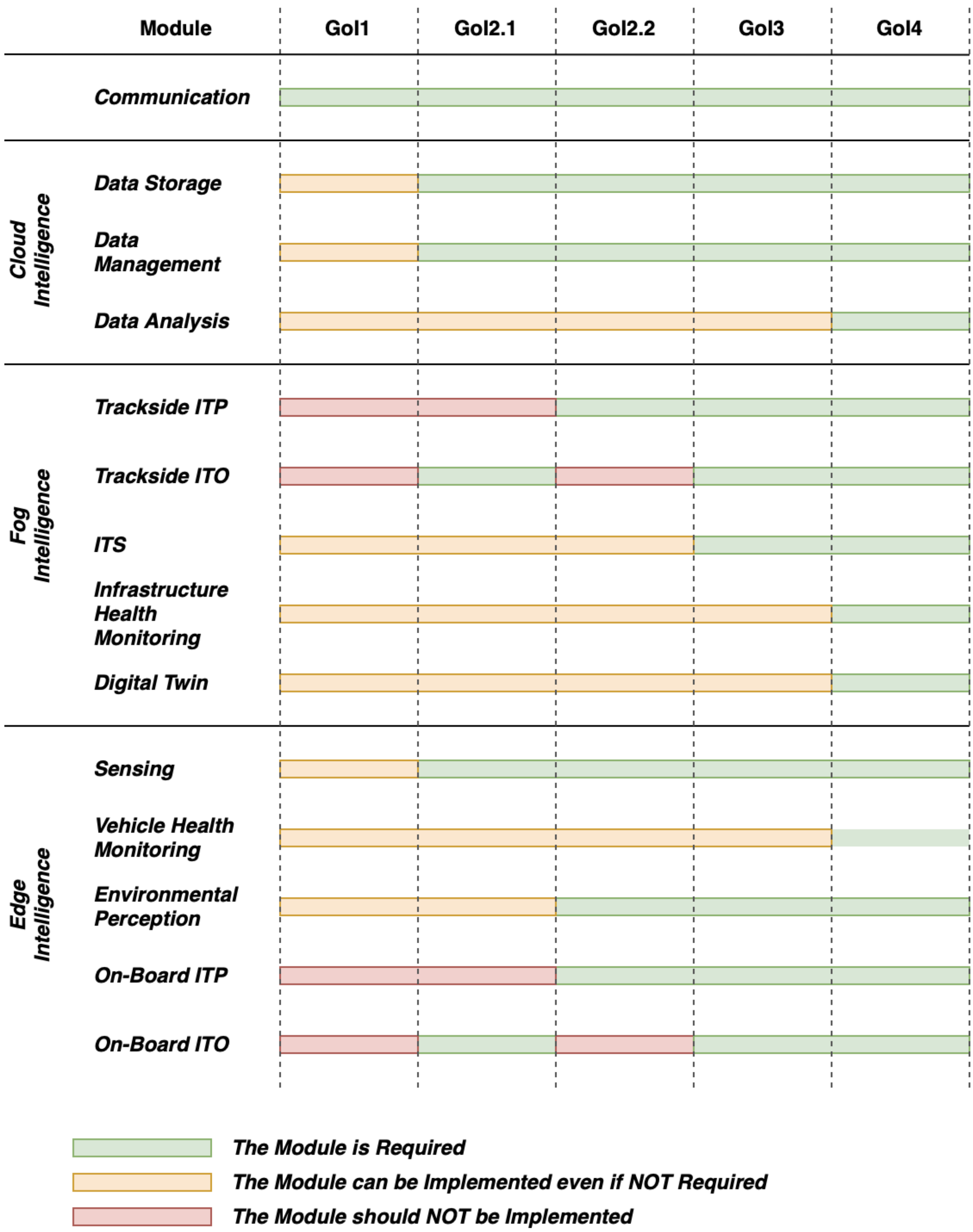

Fig. 5.7. Required Modules per GoI Level.

could be anyway implemented to add more efficiency and safety. For example, the IHM and VHM are crucial at GoI4 to create a fully-connected environment, but it can be implemented also at lower GoIs to intelligently check and continuously monitor railway assets.

To conclude, below we list a series of milestones that should be reached in order to move towards full autonomy. These milestones result from the survey and the research activities performed when developing the two WP2 PoCs, therefore, there may be other important milestones to be analysed in the future that are not included herein. We clustered these milestone into the macro areas of **Regulatory** / **Safety Needs** and **Technical Needs**:

- **Regulatory / Safety Needs:**
  - Secure IT Systems;
  - Available and Reliable Communications;
  - Extremely Reliable Vehicle Interactions;
  - Reliable Train Position Computations;
  - Exact Knowledge of Train Paths;
  - ATP as Safety Envelope;
  - Explainable and Stable AI Models;
  - Ad-hoc Verification and Validation Methods (e.g., Digital Twins-in-the-Loop);
  - Ad-hoc Standards and Regulations.
- **Technical Needs**
  - Data Availability and Correctness;
  - Energy-Efficient AI Models;
  - Real-Time Computations and Hazards / Obstacles Identification;
  - Reliable Hazards Detection Mechanisms;
  - Reliable and Cost-Effective On-board / Trackside Sensors (Low-Latency and Correctly Calibrated Sensors);
  - Effective Sensor Fusion;
  - Integrated Cognitive Digital Twins for Infrastructure / Vehicle Health Monitoring.

6. Integrating AI in Railway Maintenance and Inspection

6.1. Introduction

As analysed during the first phases of the project (WP1), the Railway Area of Maintenance and Inspection has been the most investigated by researchers and practitioners. Several solutions have been proposed to shift from corrective to predictive maintenance.

To generalise, inspections are typically conducted on the field by human operators. If we take as an example the railway track inspections, these are typically conducted during the night (when the traffic is suspended) and through costly maintenance vehicles/tools which are adopted to scan all the components of the railway line to check for defects/failures. This is just one of the multiple inspection activities (e.g., trains' components checking, level crossing inspections, etc.) that are conducted on a scheduled basis (i.e., once every week, month, etc.) which seems not to be that efficient, especially when it comes to promptly detecting defects so that they would not harm either passengers and other railway assets. Indeed, malfunctions could happen between two subsequent inspection activities leading to unpleasant consequences.

With the advent of AI, it has been noticed that it would be possible to start monitoring assets in a continuous way and to shift *from scheduled inspection and corrective actions to continuous monitoring and predictive maintenance*. Several extremely promising approaches have been proposed in the literature [16–18] to move towards this direction. Following this line, within the RAILS project, we have focused on two PoCs to investigate how AI could be introduced within railway assets smart maintenance: "Smart Maintenance at Level Crossings" and "AI-based Rolling Stock Rostering". The first PoC was oriented at understanding to what extent it would be possible to exploit AI (specifically Deep Learning) and non-intrusive sensors (e.g., cameras and microphones) to continuously monitor the health status of a level crossing; while the second was oriented at exploring the capability of exploiting Reinforcement Learning techniques (e.g., Deep Q-Networks) into rolling stock circulation scheduling and predictive maintenance tasks, in order to optimise and enhance the current non-flexible maintenance policy and paradigms.

The findings and considerations coming from the aforementioned PoCs, together with the answers to the Roadmapping Survey introduced in the previous sections, converged into the analysis of the topics discussed in the following of this chapter. To be specific, Sections 6.2 and 6.3 summarise and discuss the results of the Roadmapping Survey, analysing the answers related to the topics concerning Railway Maintenance and Inspection, i.e., "Intelligent Audio-Video Technologies for Non-intrusive Infrastructure Inspection" and "Intelligent Digital Twins for Predictive Maintenance of Railway Assets". Then, Section 6.4 provides considerations about the introduction of AI into Railway Maintenance and Inspection activities by taking into account survey results and the findings obtained throughout the whole RAILS project.

6.2. Intelligent Audio-Video Technologies for Non-intrusive Infrastructure Inspection

Most railway assets/systems are involved in safety-critical functionalities. Their continuous monitoring and the prediction of possible failure/defects may allow for safer operability of the whole sector. In order to achieve that, adequate sensors must be installed to collect relevant information. From a very high-level perspective, sensors may be subdivided into two main macro-categories:

- *Intrusive Sensors*, i.e., sensors which are installed directly on the component or within the system that is intended to be monitored. Examples are accelerometers, voltmeters, and so on.
- *Non-Intrusive Sensors*, i.e., sensors that can be installed externally to the system without interfering with its operability. Examples are microphones and cameras, which have been the focus of this topic and the Level Crossing PoC.

Assets deployed recently may be already equipped with the adequate *intrusive* (but expected by design) IoT sensors. However, those that have been deployed decades ago may be not. Concerning the latter, in order to implement predictive maintenance (or similar application), actions would be required to equip them with the adequate set of sensors allowing for their *intelligent* monitoring. Two main paths can be identified: i) install intrusive sensors with the risk of running into re-approval processes (especially in case of safety-critical assets); and ii) adopt, *when possible*, non-intrusive sensors to potentially extract about the same information that would be extracted by means of intrusive ones but without interfering with assets operations. Clearly, the latter is viable only in case the defects/anomalies to be detected would be recognisable by means of non-intrusive sensors; for example, cameras can be adopted to detect visible defects (e.g., cracks, missing objects, and so on), while microphones can be leveraged to identify anomalies that can be recognised by detecting specific audio patterns (e.g., understanding whether the warning bell of a level crossing is ringing as it should and is properly audible).

Within the RAILS project, we investigate the second path by taking Level Crossings as reference assets. Then, through the Rodmapping Survey, we asked several railway experts to provide us with their vision of the current level of maturity of Intelligent Audio-Video Technologies for Non-intrusive Infrastructure Inspection, when they expect these technologies to be mature enough for operational uses, and which are the main criticalities/obstacles that must be addressed to achieve full maturity. The results are discussed below.

6.2.1. Estimated Maturity Level and Time to Full Maturity

Figures 6.1 and 6.2 respectively report the distribution of the answers the participants gave to the questions: considering the topic “Intelligent Audio-Video Technologies for Non-intrusive Infrastructure Inspection”, i) *“How do you estimate the current Technology Readiness Level (TRL)?”* and ii) *“When do you expect the technology to be commercially available (TRL 9)?”*. In the figures, IDK stands for “I don’t know”.

As for the current maturity level, TRL5 has been the most voted, however, there has also been a wide consensus around TRL7 and even TRL9 meaning that, in some circumstances, these technologies are already implemented in the field. The estimation of the time to full maturity is in line with the TRL predictions, indicating that Intelligent Audio-Video Technologies for Non-intrusive Infrastructure Inspection will be potentially available in less than 5

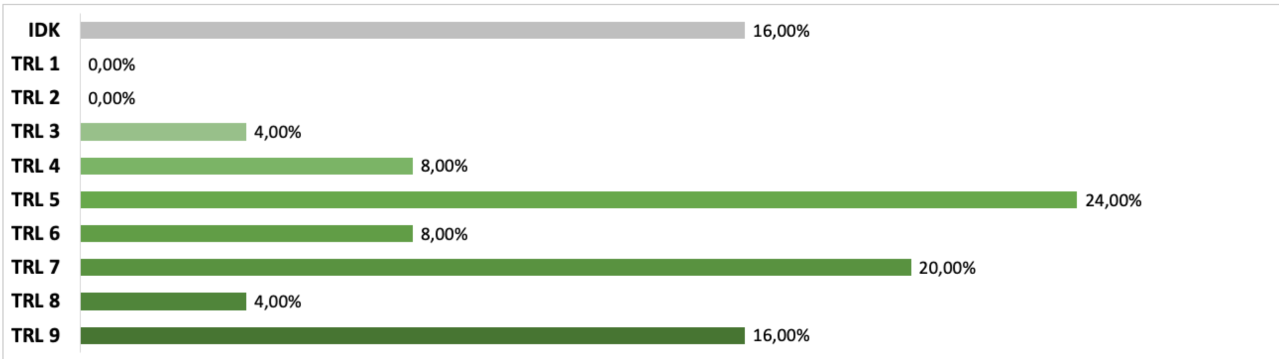

Fig. 6.1. Intelligent Audio-Video Technologies for Non-intrusive Infrastructure Inspection: Estimated Maturity Level

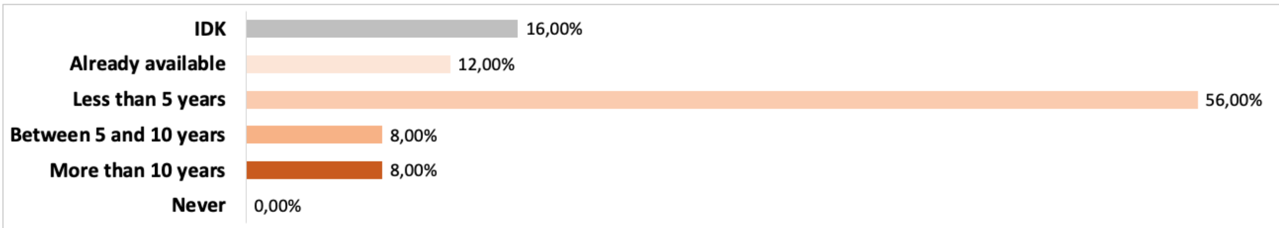

Fig. 6.2. Intelligent Audio-Video Technologies for Non-intrusive Infrastructure Inspection: Expected Time to Full Maturity

years.

6.2.2. Current Criticalities

To support the answers in Figures 6.1 and 6.2, participants were also asked to *"indicate the main criticalities the should be overcome"* in order to implement "Intelligent Audio-Video Technologies for Non-intrusive Infrastructure Inspection".

A number of criticalities were identified, which can be clustered as follows:

- **Implementability Issues.** This includes all the possible issues that could affect the actual implementation of intelligent monitoring systems. Two sub-clusters can be identified:
  - **Sensors-oriented Issues**, including, among others: i) *the costs of the sensors and their installations* and, consequently, the *investments* that Infrastructure Operators should face to sensorize railway assets; ii) the *need for dedicated sensors for each specific task*; and iii) *the maintainability of sensors*, for example, cameras whose lenses can become dirty over time.
  - **Task-oriented Issues**, encompassing, but not limited to: i) *the variety of possible visible defects*, i.e., the fact that assets could result to be defective in disparate modes which may not be all accurately catalogued; ii) *the different geometrical and perspective alignment of defects/anomalies*, e.g., some defects are visible from certain camera angles but not from others; and iii) the *availability of defective/faulty samples*. All these factors clearly depend on the specific task that should be addressed, nonetheless, they should be always taken into account as they could heavily affect the implementability, and consequently the performance,

of AI systems.

- **Performability Issues.** This includes all the factors that could reduce the *accuracy* and the *reliability* of AI models. For example, some AI models are not capable of correctly detecting **small-scale defects** or there may be some *noise patterns* that could lead to miss-classifications / miss-detections.

In addition to that, there are a few other aspects that came out from the survey which could obstruct the implementation of such intelligent maintenance systems:

- First, as partially mentioned above, the implementation of a specific AI system depends on the specific task it has to address. Therefore, these technologies should be most likely investigated use-case by use-case. The difficulties, in this context, are related to the fact that specific data configurations may be identified for each piece of equipment to be monitored.
- Second, the introduction of these technologies may be easier on new assets (as already mentioned at the beginning of this chapter) rather than old ones. Most likely because the former could be equipped with adequate sensors starting from the design phase.
- Third, it should be found the right balance between on-board and trackside equipment. Also, standardised ways would be required to prepare railway assets in order to facilitate the identification of defects/malfunctions.
- Fourth, validation and certification procedures would be a central point also for maintenance applications. In addition to that, dedicated AI models should be developed instead of using open source models (e.g., YOLO).
- Lastly, if infrastructure inspection will become reliant on AI, especially if there would not be any human-AI collaboration but the processes would be fully automatised, building public trust in these systems will be crucial. Transparent communication about the benefits, limitations, and safety measures of intelligent audio-video technologies can help to increase public acceptance.

6.3. Intelligent Digital Twins for Predictive Maintenance of Railway Assets

From a theoretical perspective, a Digital Twin (DT) can be defined as a digital representation of a physical asset which is connected to and evolves with its physical counterpart thanks to IoT monitoring devices [19]. Instead, an AI-aided (or Intelligent) Digital Twin (AIDT) is a DT that integrates AI functionalities to, for example, learn how to behave like the physical counterpart, or pre-processing data coming from IoT sensors. This kind of DTs could open opportunities like the possibility of obtaining a digital version of an asset that can be solicited with various inputs (even potentially hazardous) to understand what would happen in the real world under given circumstances (without hurting anyone or anything).

Through the Rodmapping Survey, we asked railway experts to provide us with their vision of the current level of maturity of Intelligent Digital Twins (with a specific focus on predictive maintenance of railway assets), when they expect this technology to be mature enough for operational uses, and which are the main criticalities/obstacles that must be addressed to achieve full maturity. The results are discussed below.

6.3.1. Estimated Maturity Level and Time to Full Maturity

Figures 6.3 and 6.4 respectively report the distribution of the answers the participants gave to the questions: considering the topic "Intelligent Digital Twins for Predictive Maintenance of Railway Assets", i) *"How do you estimate the current TRL?"* and ii) *"When do you expect the technology to be commercially available (TRL 9)?"*

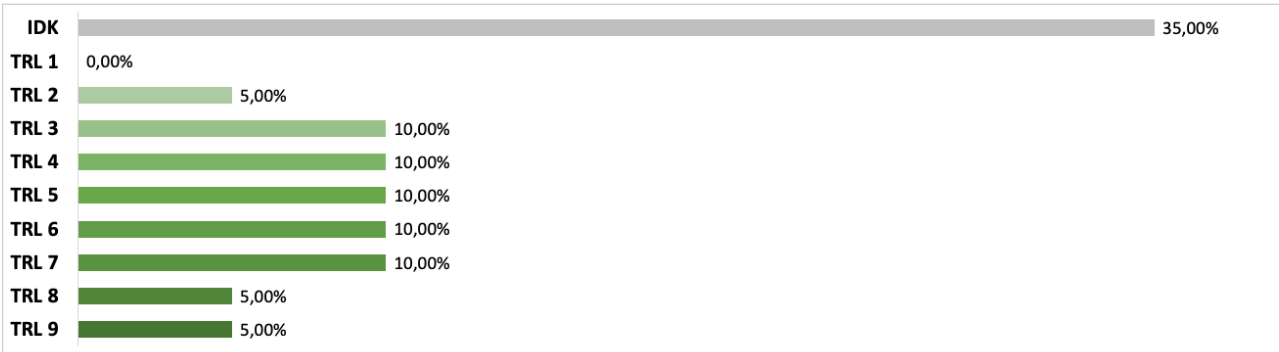

Fig. 6.3. Intelligent Digital Twins for Predictive Maintenance of Railway Assets: Estimated Maturity Level

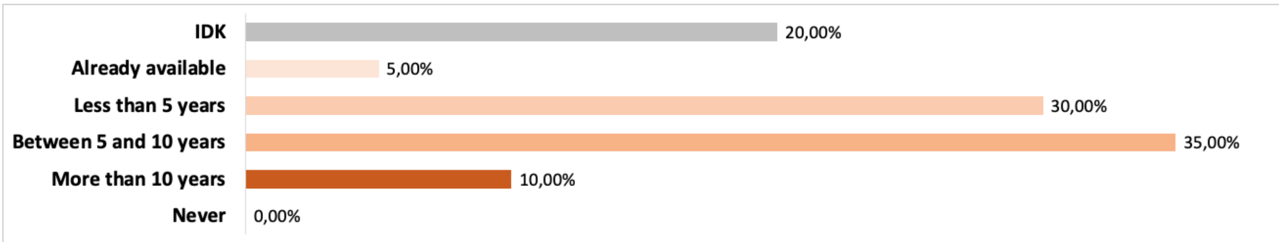

Fig. 6.4. Intelligent Digital Twins for Predictive Maintenance of Railway Assets: Expected Time to Full Maturity

As for the current maturity level, differently from the other topics discussed in this document, in this case, a number of participants abstained. All other results are more or less equally distributed from TRL2 to TRL9. However, from the discussion, it emerged that this would be an extremely relevant technology to further innovate railway maintenance activities and it would be potentially available in less than 10 years.

6.3.2. Current Criticalities

As for the previous topic, to support the answers in Figures 6.3 and 6.4, participants were also asked to *"indicate the main criticalities that should be overcome"* in order to implement "Intelligent Digital Twins for Predictive Maintenance of Railway Assets".

Also in this case, different challenges were identified which can be clustered as follows:

- **Implementability Issues.** The process of development of DTs is quite challenging, especially if we consider the *heterogeneity of multiple instances of the same railway asset*. Hence, it may be challenging to build *general* and *reproducible* DTs that could suit for multiple railway assets. In addition, another challenge is posed by the fact that the *DT software should be maintained* over time. Continuing, DTs require to be *constantly updated in real-time* in order to properly represent their physical counterparts;

this would result into *massive data acquisitions* that *could not be trivial to manage*. To conclude, also the *training of AI algorithms may introduce complexities* especially if those must *continuously learn* from new data and *adapt to changing* operating conditions.

- **Representativity Issues.** *Correctly representing the reality* through a DT is challenging (*reality gap*). It may be not trivial to *properly estimate model parameters*, also, *linking real and virtual world may be costly*.
- **Interoperability Issues**. The same component developed by different stakeholders may have different characteristics depending on the stakeholder itself. The same would go for DTs developed for a specific component, which could be different depending on the specific stakeholder that developed it. *Interoperability among vendors and stakeholders* is then one of the key challenges to be overcome for the effective development of intelligent DTs. To potentially overcome interoperability issues and, thus, effectively leverage DTs, *standardised identification methods* should be identified.

Another aspect that emerged from the survey is related to **data availability and sharing** among various stakeholders. Basically, sharing operational data with component producers would allow them to deliver extra value as they could optimise practices and development processes. In this context, *data sharing models* would promote the integration of DT within railways.

To conclude, interestingly, some of these challenges are in line with those we identified within our works on AIDTs for railway assets maintenance [19, 20] which include *interoperability*, *connectivity*, *data privacy and security*, and *scalability* (i.e., the problem of integrating and managing multiple DTs as a unique and larger DT).

6.4. Future Research Directions

Basing on our research and the survey results, the Maintenance and Inspection area is one of the most investigated for the application of AI approaches in railways. Different solutions have been proposed to support the paradigm shift from corrective maintenance and scheduled inspections to predictive maintenance and continuous monitoring, with some of these technologies that seem to have already reached a certain level of maturity allowing them to be identified as TRL9. Nonetheless, as also emerged from the survey, there are so many different maintenance tasks that specific considerations can be made only use-case by use-case.

From a high-level perspective, however, it is possible to identify three main “maintenance types” centred on AI that are sufficiently general and could apply to any railway asset:

- **Type 1**: No AI is involved.
- **Type 2**: AI is used to predict/detect possible assets’ failures/defects.
- **Type 3**: AI is used also in combination with DTs to intelligently model assets’ behaviour and perform in-depth analyses on assets’ evolution.

Important underlining, these types have to be considered from the perspective of “AI introduction in railway maintenance applications”. For the sake of clarity, it is not said that DTs are based on AI, therefore, in this classification, they can also be considered within Type 1 and 2 but, in these cases, they are not supported by AI functionalities.

The gap between Type 1 and Type 2 is already being filled, different approaches have been investigated to introduce AI in railway maintenance applications [17, 18] (as also analysed in the previous phases of the RAILS project); also, as emerged from the survey, in some specific cases this gap seems to have been already closed (i.e., these technologies have reached TRL9).

Conversely, the gap between Type 2 and Type 3 seems to deserve further investigation. Within the RAILS project, we tried to formalise some concepts in relation to AIDTs which we summarise below with the hope that they could be relevant to support this shift and future research.

Contextualising AI-aided Digital Twins. From a high-level perspective, AI and DTs can "support each other" in two main ways: i) through DTs it would be possible to generate synthetic data (e.g., by adopting injection approaches [21]) to train and test AI models; and ii) AI could extend DT functionalities from data pre-processing to the deployment of intelligent services (e.g., predictive maintenance) [20]. In this document, as mentioned above, we refer to the latter as "AI-aided Digital Twins" (AIDTs), i.e., DTs whose capabilities (part of them) are empowered by AI.

DT Design and Development Guidelines. By taking advance of the literature on DT design methodologies, in [20], we formalised some step-by-step guidelines that could support DT design for railway predictive maintenance applications. Herein, we recall and briefly summarise these guidelines (schematized in Fig. 6.5); reference [20] can be visioned for further details.

The guidelines are provided as a workflow including twelve main tasks: the first six tasks (in blue in Fig. 6.5) relate to the design of the DT and its service(s) - predictive maintenance, in this case - while the other tasks (in green in Fig. 6.5) identify the development and deployment of the service. The tasks are:

- **Requirement Specification.** Steps within this task identify the primary information/requirements that will be at the basis of the DT design including the reference industry, the purpose of the DT (together with functional requirements), the asset/process to be replicated, and the technologies required for the DT development.
- **Process Planning.** This task identifies the functionalities and the properties of the Physical Twin (PT) that should be modelled through the DT. Then, it defines what data are required for this purpose and, consequently, the communication infrastructure required to get the data from the PT.
- **Architectural Design.** Steps within this task define architectural patterns and identify components for the design of the DT. Also, if the DT should be dynamic – i.e., its architecture would adapt over time to system changes – ad-hoc architectural solutions are identified.
- **Digital Representation.** This task defines how the PT should be modelled to replicate, as faithfully as possible, all its properties and behaviours.
- **Digital Twinning.** This is the core task for DT design. It defines the DT infrastructure by generating the PT models (whether manually or automatically), making sure that these models and other possible components are properly integrated, and tuning and validating them.

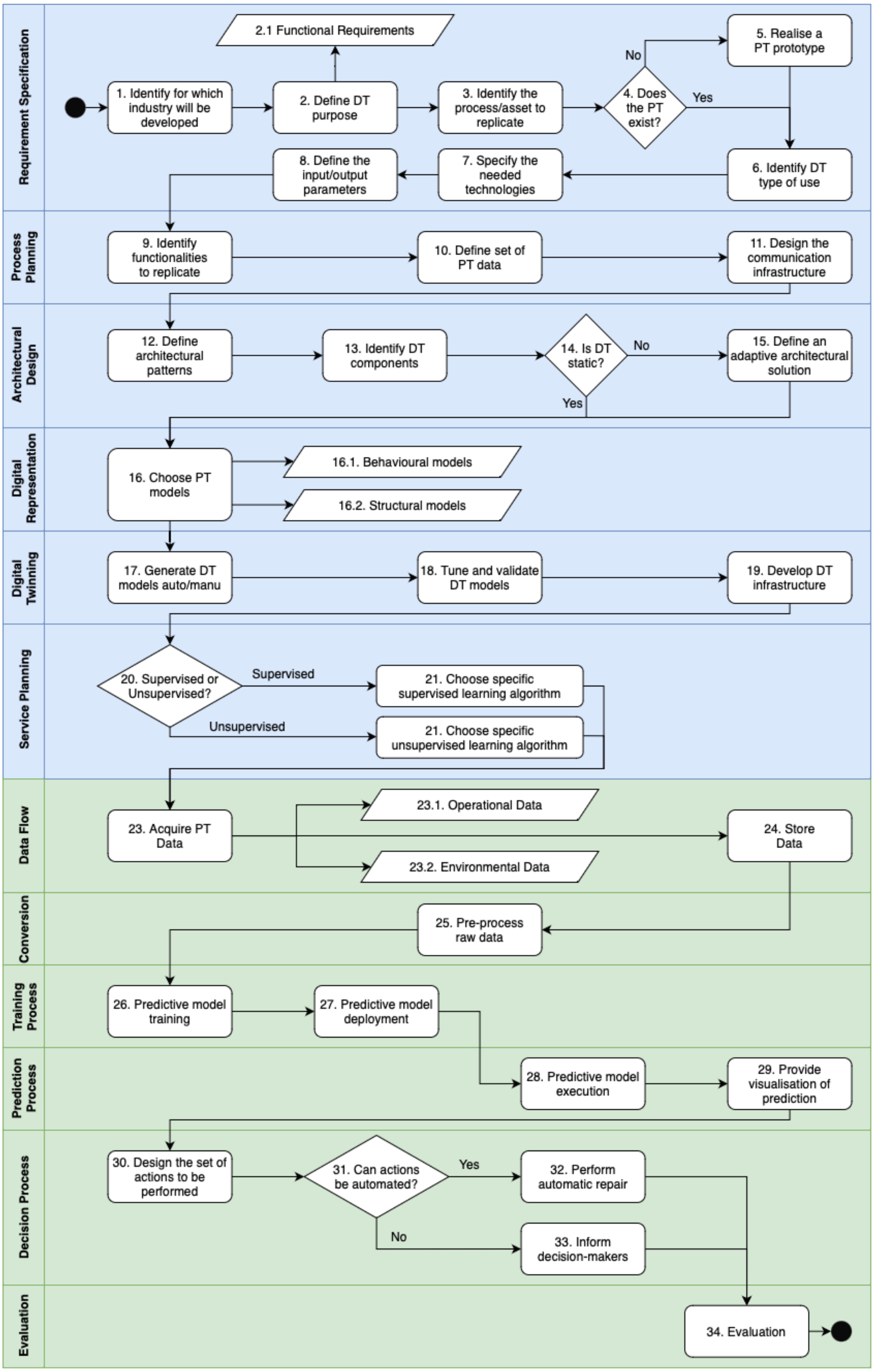

Fig. 6.5. Guidelines for the Design and Development of AIDTs. Excerpted from [20].
DT = Digital Twin — PT = Physical Twin

- **Service Planning.** Once the DT is implemented, this task designs the service(s) that the DT should provide. The example, in this case, is the implementation of a predictive maintenance application that leverages the DT. Therefore, the learning paradigm (supervised/unsupervised) and the specific learning approaches are identified.

- **Data Flow.** This creates the bidirectional connections between the DT and the PT leveraging the communication infrastructure identified above. Then, it creates, indeed, the data flow by combining the stream of operational and environmental data with historical ones (i.e., those already stored) and saves everything into appropriate storage solutions (e.g., local/cloud).
- **Conversion.** This task pre-processes (e.g., clean, fuse, modify, homogenise) all collected data.
- **Training Process.** Steps within this task are oriented at training the learning algorithm(s) identified above in this framework on the pre-processed (if required) data and then, once the predictive model has been properly characterised, to deploy it to be used at run-time.
- **Prediction Process.** The predictive model is executed at this stage and used to analyse real-time data coming from the PT to check whether malfunctions are going to occur. Predictions are then processed to be properly visualised.
- **Decision Process.** On the basis of the predictions, this task defines the actions to perform on the PT. Actions are then performed manually by human operators or automatically by the system itself.
- **Evaluation.** At the end, the DT such implemented (together with the service(s) it provides) is evaluated by means of PoCs. Although metrics exist to evaluate prediction models, there seems to be evidence of the fact that analysing DTs through PoCs could lead to better evaluations [20].

For further details on the various tasks and steps, please refer to [20].

Preliminary Architecture for AI-aided Digital Twins. In addition to the guidelines, we also tried to formalise an example architecture for AIDTs, highlighting the main components that should be involved and where/how AI could contribute. The architecture is shown in Fig. 6.6; the **Physical Assets** represents the PT for which the DT is created.

The example architecture involves the following layers:

- **Physical Layer.** This contains the components that interconnect the physical asset to its DT. For example, *sensors* allowing real-time data collection and *actuators* implementing the decisions taken at the upper layers directly on the physical asset.
- **Data Layer.** This layer deals with data pre-processing and storage, *Knowledge Management*, and data *Presentation* (e.g., through Human-Machine Interface (HMI)). Then all information stored in this layer is used by the upper layers to perform analyses (e.g., predictions) and provide services. Worth mentioning, the *AI Pre-Processing* is one of the core components for AIDTs. Briefly, when data are collected they can be both pre-processed through *Basic Elaborations* (e.g., clean, homogenisation, etc) and through advanced AI processing methods. This would open opportunities to, e.g., extract further data from those collected through sensors.

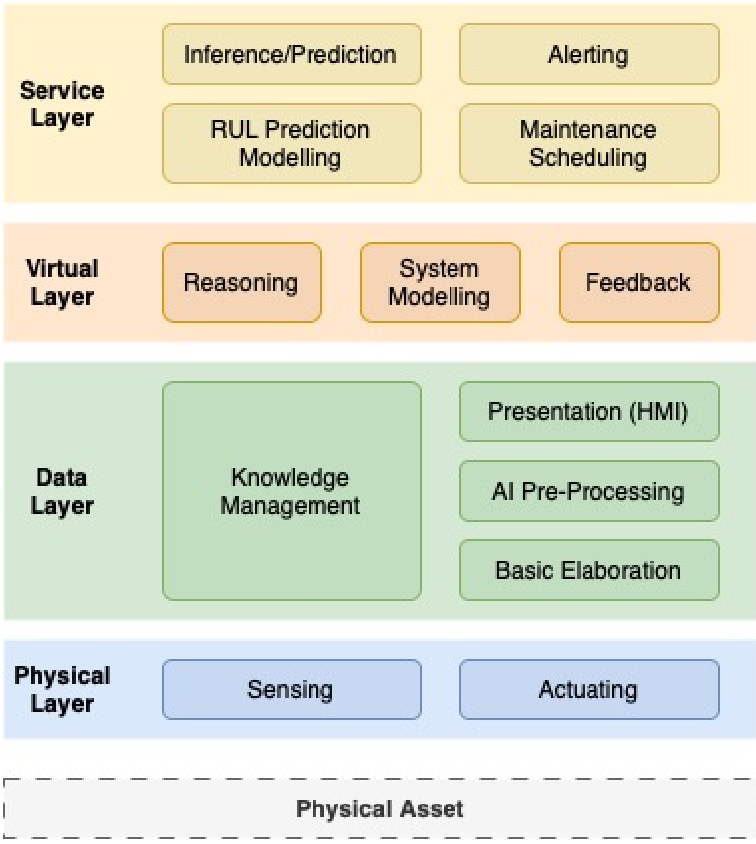

Fig. 6.6. An Example Architecture for AIDTs. Excerpted from [20].

As an example, while working at the Level Crossing PoC, we leveraged video data collected through cameras and an AI algorithm to extract the movement that the barrier traces over time. In other words, we started with video data and extracted other types of data that could then be used by the upper layer to predict, for example, the Remaining Useful Life (RUL) of the barrier.

- **Virtual Layer.** This layer includes the core components that are required to generate and manage the virtual representation of the physical asset. At this level, AI can be adopted within the *Reasoning* component – e.g., to extract useful information from data – and within *System Modelling* – e.g., to model the behaviour of the physical asset. Then, this layer also involves a *Feedback* component that serves to propagate the decisions taken at this and the Service Layer towards lower layers (e.g., to the *Presentation* component to show analyses in a human-comprehensible way).
- **Service Layer.** This layer implements the prediction and decision processes. For example, in the context of railway assets maintenance, this layer would include *Inference/Prediction* and *RUL Prediction Modelling* capabilities to detect the health status of the asset's component and possibly analyse their behaviour to estimate the RUL. Then, basing on these analyses, the *Alerting* component will, indeed, rise alerts to support maintainability, while the *Maintenance Scheduling* component will optimise the scheduling of maintenance activities.

To conclude, it is worth mentioning that the guidelines and the example architectures have been drawn in the specific context of "AIDTs for railway assets maintenance" and are not meant to be exhaustive. There may be steps or architectural components that are missing, but that could be as well important to effectively implement AIDTs. The aim of this analysis was to highlight the possibilities that AI would introduce if integrated within DTs, given that, as also emerged from the survey, this could actually be an important achievement towards the improvement of railway maintenance strategies. Hence, we tried to formalise some concepts that would hopefully be valuable for future research in this direction.

7. Integrating AI in Railway Traffic Planning and Management

7.1. Introduction

During the initial stages of the project (WP1), we found that the Railway Traffic Planning and Management Area is the second most studied area by scholars and professionals. To forecast primary and secondary delays, methods such as mathematical and stochastic models have been extensively utilized. Yet, as the amount of data grows, it becomes increasingly challenging to use historical operational data and incident records for numerical predictions of a train's delay status. The intricacy of the factors influencing train delays makes it difficult for these traditional methods to effectively forecast delays. Furthermore, any substantial aggregation of delays can negatively impact the whole railway network, compromising operational efficiency and punctuality. After a thorough review of previous studies, we found an effective approach to combine them, providing a fresh viewpoint on train delay prediction and incident analysis.

In recent years, while the frequency of initial delays in rail services has remained stable, secondary, or reactive, delays have been on the rise, presenting difficulties in understanding and management. The after-effects of a reactive delay hinge on the interactions between various trains and the characteristics of the railway network. A domino effect can occur where one reactive delay triggers others, potentially affecting numerous trains. Traditional methods struggle to predict these impacts and resulting patterns accurately. Hence, an alternative method is required to better understand the root causes of reactive delays and to estimate the potential effects of changes on service delivery.

With the advent of AI, it has been noticed that it would have been possible analysis the railway delays and make predictions in a more intelligent way and to shift *from mathematical and stochastic optimization algorithms to AI technique-based prediction/analysis models*. Several extremely promising approaches have been proposed in the literature [16–18] to move towards this direction. Following this line, within the RAILS project, we provided a comprehensive analysis of the methodological and experimental PoCs conducted for the two case studies, "Graph Embedding based Primary Delay Prediction" and "Big Data on Incident Attribution Analysis". The primary objective of the first PoC is to create a structural deep network representation for the stations in a railway network, which can be used in modelling the highly non-linear dependencies present in network topology. To achieve this, a unique deep learning model called the "Structural Deep Network Embedding approac" was proposed, drawing inspiration from successful applications of deep learning methods presented in prior works [22]. while the second was oriented at exploring the capability of exploiting Big Data for interactive delay attribution visualisation and Graph Neural Network techniques for predicting potential propagation links. We intend to train a link prediction model that can predict whether a propagation link should exist between two nodes, enhancing our understanding of delay causation and propagation.

7.2. Train Delay Prediction Using Graph Embedding

The objective of this study's delay prediction is to forecast the average delay for an unobserved train service, drawing on delay data collated from historical railway operations. This takes into account specific characteristics of individual railway stations and overarching network structures, such as station connectivity, the weightage of specific routes, and varying network densities across regions, among others. As a train's delay status at a particular station could be influenced by adjacent stations, it's crucial to understand the network connections among stations. For instance, delays are more likely to impact neighboring stations as the geographical proximity between them decreases.

Serves as an efficient technique for dimensionality reduction in the field of computer science, machine learning. The fundamental principle behind embedding is to position connected nodes nearer to each other in vector space, thereby preserving the structural relationships inherent in the original network. While each vector value lacks explicit interpretation, it partially characterizes a particular station. The utility of this representation becomes apparent when comparing the similarities between two stations. In this context, the SDNE method significantly condenses vital information, enabling efficient and reliable vector operations for machine learning-based predictors compared to traditional mathematical algorithms.

Moreover, we propose to incorporate the derived hyper node embedding vectors (i.e., nodes/stations in sequence along a specific route) into a route embedding vector. This step would further condense and aggregate structural information of the target railway network, reducing feature dimensions. The anticipated route embedding representations should meet the following benchmarks:

- Regardless of a specific route's length, the resulting route embedding vectors must maintain a uniform size
- The route representations should distinctly encapsulate the characteristics of the entire route, including the density of stations en-route, their sequence, and congestion level on the route
- Route embedding vectors should effectively preserve both local and global characteristics

7.2.1. Estimated Maturity Level and Time to Full Maturity

Figures 7.1 and 7.2 respectively report the distribution of the answers the participants gave to the questions: considering the topic "Train delay prediction using Machine Learning", i) *"How do you estimate the current Technology Readiness Level (TRL)?"* and ii) *"When do you expect the technology to be commercially available (TRL 9)?"*. In the figures, IDK stands for "I don't know".

As for the current maturity level, TRL7 has been the most voted, however, there has also been a wide consensus around TRL4 and even TRL9 meaning that, in the most circumstances, these technologies are already successfully validated and implemented in the field. The estimation of the time to full maturity is in line with the TRL predictions, indicating that Machine Learning-based Technologies for Train delay prediction will be potentially available in less than 5 years or already been commercially available in some particular operational environments.

7.2.2. Current Criticalities

To support the answers in Figures 7.1 and 7.2, participants were also asked to *"indicate the main criticalities that should be overcome"* in order to move implement "Graph Embedding and machine learning techniques into train Primary delay prediction". A number of criticalities were identified from the live event results regarding the WP4 question "what are the main

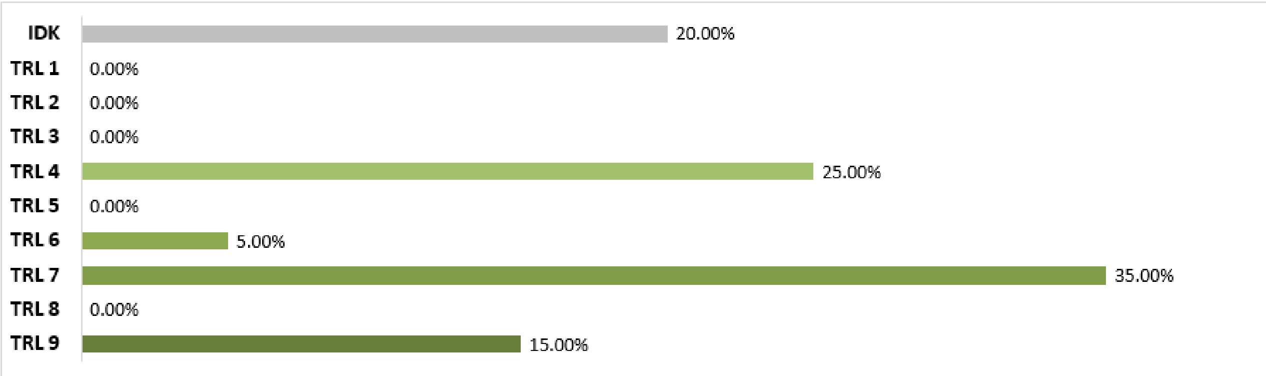

Fig. 7.1. Train Delay Prediction using Machine Learning:
Estimated Maturity Level

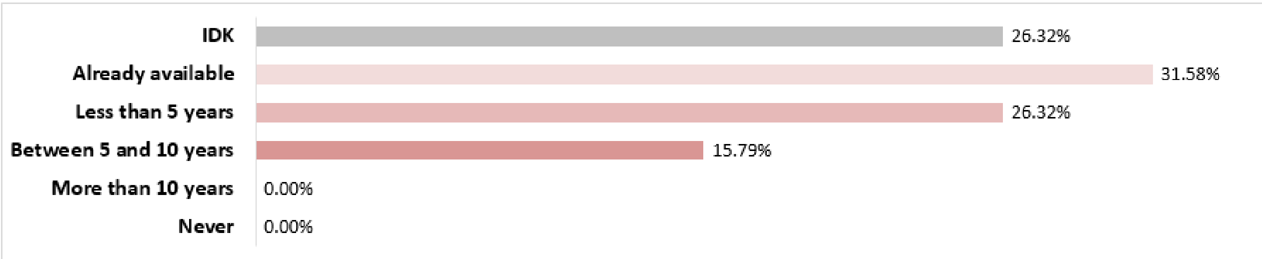

Fig. 7.2. Train Delay Prediction using Machine Learning:
Expected Time to Full Maturity

criticalities need to overcome in terms of 'train delay prediction using machine learning'?". Which can be clustered as follows:

- **Data Issues.** This covers all the possible issues that could affect the quality of chosen datasets. Specifically, it includes the *overall quality of raw data*, *data acquisition*, and *data availability*.
- **Accuracy criterion** An accurate model or acceptable prediction accuracy, especially a high consistency between the estimating delay levels and the ground truth of real-world situation, is the another significant concerns that identified from the live chat from the event participants. That is, *good estimates*, *accurate models*, *quality of field workers estimate*, and *accuracy*, etc.
- **Practical application Issues.** This includes all the factors that could hinder the implementation of proposed relevant delay prediction models. For example, *condition monitoring* and the *intended use* of AI models. Some AI models are not capable for *real-time forecasting* or there will be some trains with *no passengers* that could lead to miss-classifications/non-optimal prediction. *Evaluating major (rare) disruptions* is crucial as it allows for robust contingency planning and efficient resource allocation, thus minimizing the substantial impact these infrequent events can have on the entire railway network and its operation.

7.3. Railway Incident Attribution Analysis Using Big Data Analytics

Gaining a comprehensive understanding of how delays at specific sites affect the wider railway network is essential for both the infrastructure provider and train operators. The current TRUST [1] system, which offers delay attribution data for those trains that experience a delay of at least 3 minutes. Delays under this threshold are automatically assigned to the pertinent railway company and Network Rail without conducting an exhaustive investigation into the delay causes.

Several intricate factors such as timetable clashes and track access rights influence the scope and duration of delay spread throughout the network. Predicting these nonlinear spatio-temporal interactions accurately with conventional methods can prove challenging. Similarly, different railway disruptions and unusual incidents can have diverse triggers, with some sharing common root causes and others not. Utilizing traditional statistical analyses or descriptive models to examine all observed relationships or triggers might not accurately depict the delay propagation chain. The conducted PoC is composed of two main parts. Firstly, we leveraged Big Data techniques to interactively visualize historic train delay records, which enables recreating the process of how disturbances, disruptions, or unforeseen events initially caused and then spread delays. Secondly, we aspire to comprehend how these disturbances morph into noticeable primary delays and then disseminate along certain lines/routes of the network. Through learning from these patterns, we were intended to predict if a delay will happen or spread between particular locations, timings, and train services.

In summary, we applied Big Data for interactive delay attribution visualization and Graph Neural Network techniques for predicting possible propagation links. We planned to train a link prediction model capable of forecasting if a propagation link should exist between two nodes, thereby improving our understanding of delay origins and spread.

7.3.1. Estimated Maturity Level and Time to Full Maturity

Figures 7.3 and 7.4 respectively report the distribution of the answers the participants gave to the questions: considering the topic of “Railway incident attribution analysis using big data analytics”, i) *“How do you estimate the current TRL?”* and ii) *“When do you expect the technology to be commercially available (TRL 9)?”*

The most voted option regarding is TRL 4, while the technology is expected to be fully mature between 5 and 10 years. Notably, there may be evidence of that incident attribution analysis is not sufficiently considered or investigated neither in the level of conceptual formulation or experimental PoC demonstration.

This is also in line with the prevision that generated from a latest successful implementation of ’network effects’ in the context of delay propagation/cascading model [23], which indicates the approach using ’Epidemiological Sir Models’ is now confirmed with the adequacy of the solutions and helped quantify the influence of primary delays and the amount of time reserve in the schedules of trains of various categories on the reliability of the standard train schedule. However, while the relevant technology is not fully mature or already been partially implemented in some aspects, there are still areas for improvement. For instance, the quality and completeness of data collected can significantly impact the accuracy of incident attribution. Therefore, continuous efforts are required to improve data collection and

[1] https://safety.networkrail.co.uk/jargon-buster/trust/

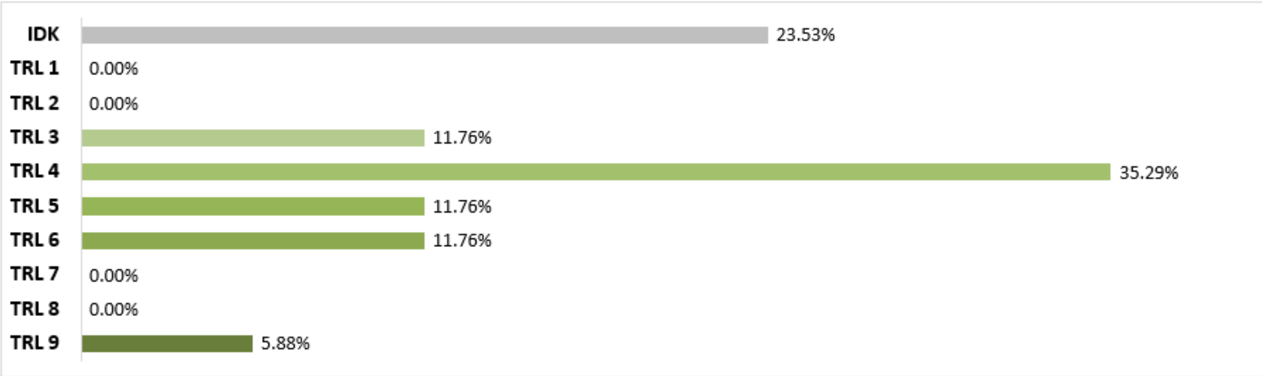

Fig. 7.3. Railway Incident Attribution Analysis Using Big Data Analytics: Estimated Maturity Level

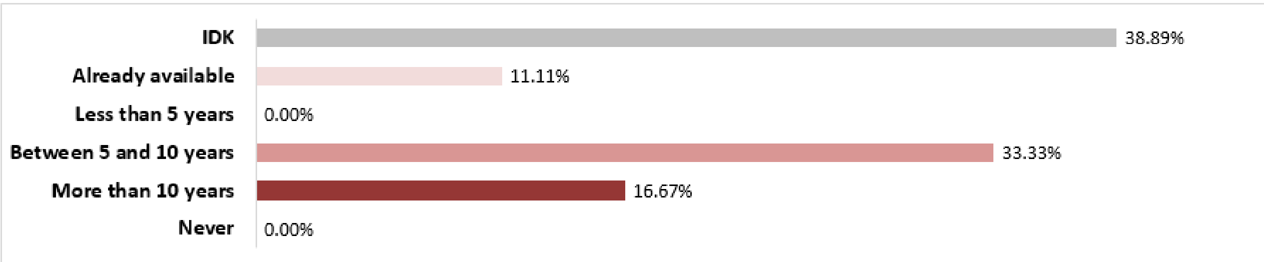

Fig. 7.4. Railway Incident Attribution Analysis Using Big Data Analytics: Expected Time to Full Maturity

processing techniques. Also, while machine learning and AI can help analyze complex relationships and patterns, the interpretation and understanding of these findings still heavily rely on human expertise. Clearly, propagation tree encompasses a plenty of critical information, and more than incident attribution task may exploit the outputs of it (e.g., further rolling stock rescheduling, track resource allocation, etc). Therefore, it would be necessary to understand if these techniques will effectively reach an adequate level of maturity in the following few years to be used in safety-critical environments such as railways. Knowing that, we asked the participants to the survey to indicate which, according to their experience, are the main issues that must be considered in order to make incident attribution analysis validated and reliable for railway environments in both practical and theoretical way; The results are reported below.

7.3.2. Current Criticalities

- **Data Issues.** It seems not to be trivial and rare - to get *enough reliable disruption/incident data* and if the obtained data *correct on the quality* largely determines to what extent the developed systems can be considered reliable. On the other hand, *ensuring data interoperability and adhering to common data standards* across various railway systems and operators is necessary to facilitate data exchange and analysis.
- **Implementability Issues.** These include choosing of *advanced models* and the need for *a agreement on a goal of attribution*, but also the problems of how to conduct an effective *model validation*. In some extreme circumstances, *large-scale disruptions* and *complexity of disruptions with several causes* may destroy the successful implementa-

tion regrading a meaningful analysis built by the past normal incident records.

- **Performability Issues.** Comparing incident attribution analysis results between different rail operators can establish benchmarks for safety and performance. Such comparisons can drive a culture of continuous improvement and healthy competition. In addition, *Fast recalculation of results based on frequent changes in line status* may also hinder the performance of the analysis results due to the large number of vehicles circulating.

In conclude, the concept of railway incident reasoning/attribution analysis is not new, but the technology and methodologies to conduct such analysis are continually evolving, becoming more sophisticated and accurate. In conclusion, the technical maturity of railway incident reasoning/attribution analysis is not relatively advanced, but there are promising directions for improvement, especially in areas like data quality, integration of diverse data sources, interpretability and accessibility of complex models, and the application of newer analytical techniques.

7.4. Future Research Directions

Based on our study and survey results, Traffic Planning and Management (TPM) ranks as the second most explored area for AI application within the railway industry. Various solutions have been suggested to aid the transition from traditional mathematical programming algorithms and stochastic optimization to AI or machine learning-based analysis and prediction. Some of these technologies appear to have achieved a level of maturity suitable for testing in specific lab environments. However, as highlighted in the survey, the diversity of TPM tasks means that each use-case must be individually evaluated.

From a broader viewpoint, we can identify three primary categories of ”delay prediction/attribution types” rooted in AI that could be generally applicable to any railway traffic management task:

- Type 1: AI is not involved.
- Type 2: AI is utilized to predict or analyze potential delay-contributing factors.
- Type 3: AI, combined with optimization algorithms, intelligently plans process behavior and conducts thorough analyses on delay evolution.

It’s crucial to note that these categories are from the perspective of ”AI introduction in railway planning and management applications.” For clarity, optimization algorithms may not necessarily be AI-based, so they could fall within Type 1 and 2, but in these instances, they are not enhanced by AI features. The gap between Type 1 and Type 2 is narrowing, as various strategies have been explored to implement AI in railway maintenance applications. In some specific instances, as suggested by the survey, this gap appears to be already bridged (i.e., these technologies have achieved TRL9). In contrast, the gap between Type 2 and Type 3 seems to warrant further investigation.

Transfer Learning Transfer learning is a powerful machine learning technique that can be highly beneficial in the context of railway networks. Essentially, transfer learning allows us to take knowledge gained from one railway network and apply it to another. This capability is especially useful when data availability is limited for a specific region or for a newly constructed rail network.

In a typical railway network, there are many common elements: trains operate under similar physical and operational constraints, and they interact with the environment in comparable ways. This means that a machine learning model trained on one network can learn valuable lessons about how delays occur, how traffic should be managed, or how maintenance schedules should be optimized. However, each railway network also has its unique features: differences in track layout, train schedules, passenger demand, and regional weather patterns, among others. These distinct characteristics can make it challenging to apply a model trained on one network directly to another.

This is where transfer learning shines. Instead of starting from scratch, transfer learning allows us to take a pre-trained model (trained on one network) and fine-tune it on another network. This way, we can retain the knowledge about general railway operations, while also learning about the specific features of the new network. For example, if we have a well-performing model trained on a comprehensive railway network in Europe and want to apply it to a newly built network in Asia with limited data, transfer learning would be a suitable approach. We would start with the model trained on the European network and then fine-tune it with the available data from the Asian network. The European model would provide a strong starting point, and the fine-tuning would adapt the model to the specific characteristics of the Asian network. Therefore, transfer learning techniques can play a crucial role in overcoming data limitations and accelerating the deployment of AI-based solutions in railway networks, ultimately leading to more efficient and reliable railway operations.

Ensemble methods Ensemble methods are powerful tools in machine learning that combine the strengths of multiple models to improve prediction accuracy and robustness. The idea behind ensemble methods, such as stacking or bagging, is that a group of models working together can often produce more accurate and reliable predictions than any single model working alone.

When it comes to predictive tasks, such as the railway delay prediction or traffic flow forecasting in our context, individual machine learning models may exhibit unique strengths and weaknesses depending on the specifics of the data and the task. For instance, some models might perform well with certain types of data but poorly with others, or they might excel in capturing specific types of patterns but miss others. Ensemble methods help mitigate these weaknesses by combining the outputs of multiple models. The collective wisdom of the ensemble is often more reliable and accurate than the prediction of any individual model. This is particularly true when the models in the ensemble are diverse, i.e., they make different types of errors due to different underlying algorithms or parameter settings. For example, bagging (short for bootstrap aggregating) involves creating multiple subsets of the original data, training a separate model on each subset, and then combining their predictions. This method can significantly reduce the variance in the predictions, leading to more robust results. On the other hand, stacking involves training multiple models on the same data, and then training a 'meta-model' to make a final prediction based on the predictions of the individual models. This allows the ensemble to learn how best to combine the individual models' predictions to achieve the highest accuracy.

In the context of railway operations, ensemble methods could be used to improve the accuracy and reliability of delay predictions, maintenance scheduling, traffic flow forecasting, and many other tasks. By leveraging the strengths of multiple models, railway operators can gain a more accurate and comprehensive understanding of their network's behavior, leading to more efficient and reliable operations.

Benchmarking and Performance Comparison Benchmarking and performance comparison are vital components of a strategy aimed at achieving continuous improvement and high standards in railway operations. By comparing incident attribution analysis results between different rail operators, it is possible to establish benchmarks for safety and performance that can serve as targets for improvement. Benchmarking allows for an objective evaluation of a rail operator's performance against industry best practices or against the performance of their peers. This comparative analysis can highlight gaps in processes, systems, or technologies, and thus provide insights into areas where improvements can be made.

For instance, if one operator consistently attributes fewer incidents to equipment failure than other operators, this might indicate superior maintenance practices or more advanced equipment. Such findings could prompt other operators to reevaluate their maintenance strategies or invest in equipment upgrades. Conversely, if an operator attributes more incidents to human error, this might highlight areas for improvement in training or operational procedures. Moreover, performance comparisons can stimulate healthy competition among rail operators. This drive to improve can lead to better safety outcomes, more efficient operations, and higher quality service for passengers. It encourages operators to not only meet the established benchmarks but to strive for excellence and set new industry standards.

By providing a clear picture of where each operator stands in relation to their peers, benchmarking and performance comparison can play a crucial role in driving a culture of continuous improvement in the railway industry. It provides an impetus for constant evolution, adaptation, and enhancement of operational standards, ultimately leading to safer, more efficient railway networks.

8. Other Findings and Directions from the Roadmapping Survey

8.1. Introduction

Besides the topics discussed in the previous chapters – which were conceived in the context of RAILS WP2, WP3, and WP4 – we also identified two other directions that could potentially benefit the introduction of AI in railways: i) "Mixed-Reality Technologies to Support AI Testing", and ii) "Sharing Relevant Datasets for Benchmarking AI Technologies for Railways". Hence, we asked the participants in the survey to share their toughs about these directions. Lastly, we also asked them to indicate the "Most Promising Future Railway Applications" that, according to them, could revolutionise the rail sector in the next 10 years.

8.2. Mixed-Reality Technologies to Support AI Testing

As introduced in Section 6.3 and discussed in our Deliverable D2.4, Digital Twins (DTs) are digital models that evolve, over time, with the corresponding physical asset. Potentially, it would be possible to create copies of a DT, representing the physical assets at a given time instant, and stress them with various inputs to predict the potential evolution of physical systems and/or generate data that can be used to train AI models. In addition to that, DTs can also support the development, validation, and testing of railway systems [24]. They could help to overcome, at least in the first phases of development, some challenges introduced by on-field tests including elevated costs and time required, limited scenarios, and high risk in case of failures.

Intelligent Digital Twins would introduce several opportunities in this direction as these kind of DTs not only evolve with their physical counterpart but would also be able of simulating their behaviour. They can be exploited, especially if combined with Mixed Reality (MR), to evaluate the behaviour of systems similar to what happens with Hardware-in-the-Loop. As spotted within the Automotive field, MR has shown great potential in linking physical vehicles with their digital counterparts making both of them susceptible to events occurring either in the real or in the virtual world [25, 26]. As a simple example, this can be exploited in the rail sector to test the physical reaction of a train (running on an obstacle-free track) and its obstacle detection system to obstacles (of any kind and in any position) which are not physically on the tracks but are simulated in the virtual world (see Fig. 8.1).

We asked survey's participants whether this technology would be useful for the rail sector and when they expect it to be fully mature to be actually implemented; results are reported in Figures 8.2 and 8.3 respectively.

According to the survey's results, such technologies would be extremely useful in railways, also because AI models must demonstrate robustness and adaptability to different conditions and Mixed-Reality could enable testing under a wide range of conditions (e.g., light changes, user interaction, etc.). In addition, about half of the participants believe that Mixed-Reality Technologies will be available in less than 5 years.

Given the attention this topic caught during the survey, we believe that Mixed-Reality Technologies and Digital Twins would deserve further investigation.

Fig. 8.1. DT-in-the-Loop and Example of Mixed Reality.

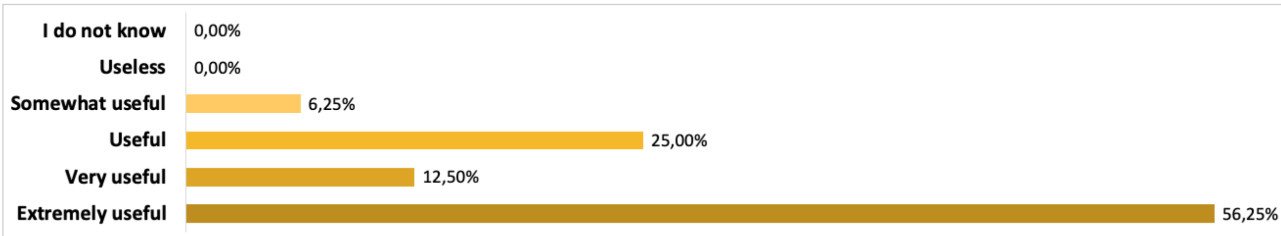

Fig. 8.2. Can “Mixed-Reality Technologies to Support AI Testing” be useful for railways?

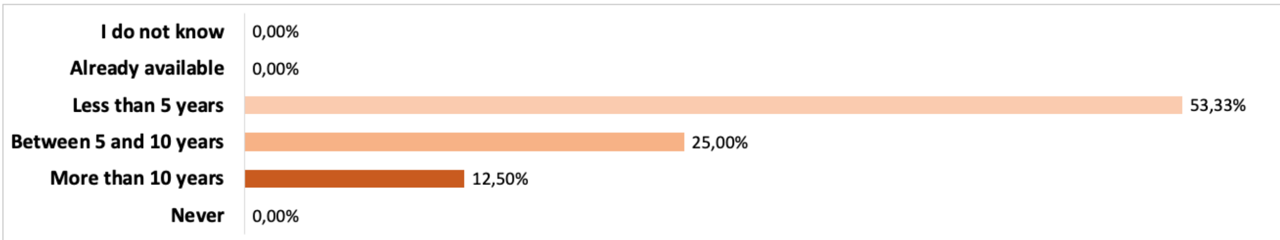

Fig. 8.3. Mixed-Reality Technologies to Support AI Testing:
Expected Time to Full Maturity

8.3. Sharing Relevant Datasets for Benchmarking AI Technologies for Railways

As emerged from the research conducted in our past deliverables, data availability and quality are two of the main issues affecting the development of AI models in railways; not only because without data it is not possible to train AI algorithms, but also because AI solutions oriented at solving the same problem but trained and tested on datasets with different characteristics are not trivial to compare. Hence, in Deliverable D2.4, we proposed a series of recommendations to try to overcome these issues which converged, eventually, into *“A Vision of a European Railway Lab for AI Applications”*, whose data-centric vision is shown in Fig. 8.4 for the sake of simplicity. For further information on this topic, please refer to Deliverable D3.4.

Then, we asked the survey participants if the sharing of datasets to train/test AI models and to be used as benchmarks (i.e., to compare and possibly elect the most performing AI solutions) would be useful for the development of AI applications in railways. As expected, almost all of them believe that such an approach would be very/extremely useful (see Fig. 8.5).

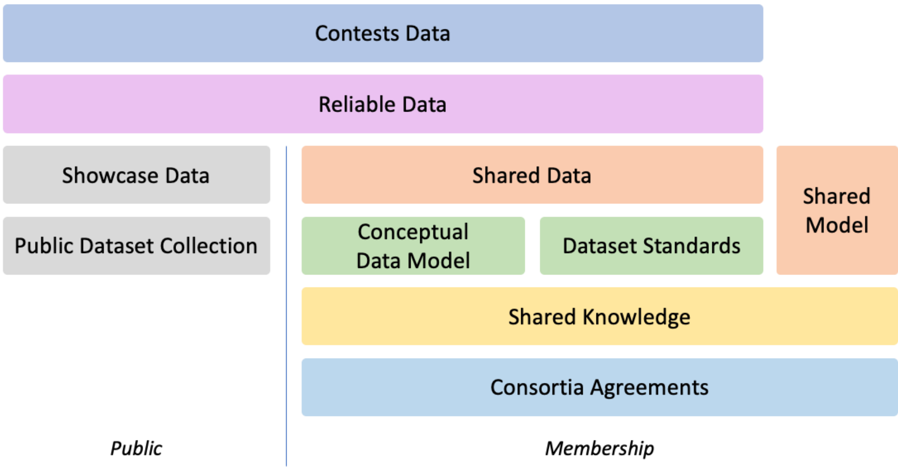

Fig. 8.4. A data-centric view of an AI European Lab for joint research in railways

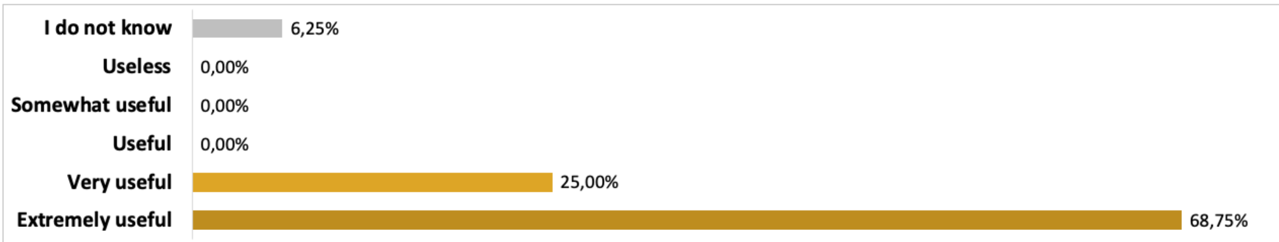

Fig. 8.5. Can the "Sharing Relevant Datasets for Benchmarking AI Technologies for Railways" be useful for railways?

Although some publicly available datasets exist (e.g., [18, 27, 28]), two of which have been made publicly available in the context of this project (i.e., Level Crossing Warning Bell Dataset[1] [29], and a dataset for Vision-Based Obstacle Detection on Rail Tracks[2]), data sharing is not always feasible as pointed out by the participants to the survey. Different aspects and issues should be considered:

- Nowadays, **Data are valuable assets for companies**; too much profitability is linked to the possession and the analysis of data. Therefore, it would not be convenient, *commercially* speaking, to disclose them.
- Data may be **confidential** and/or *sensitive*. Hence, mechanisms to ensure *privacy* should be taken into account.
- Data **quality**, **completeness**, and **fairness** must be ensured. Also, eventual **biases** that could compromise the effectiveness of AI systems should be properly managed.
- Data **diversity** may also be an issue. Collecting and integrating data from multiple sources may be challenging. Nevertheless, diversity may also introduce opportunities;

[1] https://zenodo.org/record/7945412
[2] https://zenodo.org/record/7924875

for example, integrating data from multiple sources (which could have different characteristics) could help to *reduce the bias* characterising data coming from a specific source.

These issues would be challenging to overcome, however, as also witnessed by the survey's results, we think that data sharing could be essential for the fast take-up of AI applications in railways. Perhaps, as discussed in Deliverable D2.4 and as also emerged from the survey, railway stakeholders' partnerships could foster data sharing, drive innovations towards advanced AI technologies, and create mutually beneficial collaborations.

8.4. Most Promising Future Railway Applications

To conclude, we asked the participants of the roadmapping survey to indicate which, according to them, would have been the "most promising AI applications to railways in the next 10 years" that deserve deeper investigation in the next few years. The answers are reported/clustered herein:

- *Autonomous driving* and *driver advisory* systems.
- *AI-driven signalling systems* (optimise train movements, reduce delays, and improve safety by dynamically adjusting signals based on real-time conditions).
- *Passenger companions* and applications oriented at *providing customers with targeted information* (e.g., disruptions) and *improving passengers comfort*.
- *AI-powered sensors* and *Computer Vision applications for visual inspection* to continuously monitor railway infrastructure to detect anomalies, defects, and potential safety hazards in real-time.

Together with these, two additional directions were given by the participants. These are not strictly related to the railway domain, however, are essential for the integration of AI:

- *Explainable AI (XAI) approaches*. In safety-critical applications, XAI would play a central role. Understanding the reasoning of AI systems will improve trustworthiness and facilitate human oversight.
- *Dealing with public acceptance and awareness*. Public acceptance and awareness could be another issue for the introduction of AI in railways. Educating customers about the benefits and safety measures of AI technologies could help overcome resistance and build support.

9. Conclusions

The RAILS project has undertaken a comprehensive roadmapping process to explore the integration of AI within various aspects of the railway sector. The project's journey has encompassed diverse realms, including safety, automation, maintenance, inspection, and traffic planning and management. Within each realm, the project conducted assessments of the scientific, industrial, and regulatory landscapes, outlined guidelines for transferring AI approaches from other sectors, and proposed pilot case studies to develop and experiment with innovative applications. Proofs-of-concept have been developed within the pilot case studies with the aim of identifying the required shifts and providing recommendations for effective and fast uptake of AI techniques in railways. From the roadmapping activities has emerged that the railway industry is keeping up with the times in the usage of artificial intelligence, appearing to be in step with the possibilities it offers, although several issues still remain. The project has produced valuable knowledge and pinpointed specific research directions towards autonomous trains,enhanced safety, and optimized operations, so contributing to shaping the future of railways.

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