D6.3 AI IN FUTURE METRO OPERATIONS

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Executive summary

This deliverable summarizes the outcomes of Task 6.1 and provides a comprehensive review of the current landscape of Data Science, Machine Learning (ML), and Artificial Intelligence (AI) applications in the context of future metro operations. It introduces and contextualizes the foundational concepts of pillars of Work Package 6 — and explores the anticipated impact of the European Union AI Act on the development and deployment of AI-related use cases within this domain, as outlined in Section 2.

Drawing on extensive desktop research, the deliverable reviews a curated selection of key industry reports and publications focused on the role of AI and data science in public transport. It identifies and analyses relevant trends, existing applications, and use cases that have emerged in the sector. Furthermore, it examines the current state-of-the-art in metro operations and AI integration from the perspective of a train manufacturer, offering insights into ongoing innovation and technological advancements. This analysis is complemented by the findings of two industrial workshops — one conducted with a train operator and the other with several European metro operators — which provided practical, real-world perspectives and industry needs related to AI implementation (as covered in Section 3).

Building on this foundation, the deliverable provides a detailed examination of four representative AI use cases in metro operations: crowding prediction, demand forecasting, timetable creation support, and anomaly detection, with a specific example focused on uncleanliness detection. These use cases, grounded in existing academic and industry literature, illustrate the potential of AI technologies to enhance operational efficiency, passenger experience, and service reliability (Section 4). To move from concept to practice, these use cases are further developed through detailed implementation concepts, considering architectures, data requirements, technical challenges, and potential integration pathways (Section 5).

Finally, the deliverable concludes with a synthesis of lessons learned, highlighting best practices for successful AI adoption in metro systems and identifying key technical, organizational, and regulatory challenges that must be addressed to ensure effective deployment (Section 6).

KEYWORDS

Machine Learning (ML), Artificial Intelligence (AI), Data Science, Metro Operations

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LIST OF ABBREVIATIONS AND ACRONYMS

Acronym	Meaning
AI	Artificial Intelligence
ARIMA	Autoregressive Integrated Moving Average
ASAP	As Soon As Possible
AWOR	Allowable Waiting Occurrence Rate -
B2B	Business-to-business
B2C	Business-to-Consumer
CBTC	Communications-Based Train Control
CCTV	Closed-Circuit Television
CNN	Convolutional Neural Network
DPC	Data Protection Controller
DPIA	Data Protection Impact Assessment
DPO	Data Project Officer
EC	European Commission
EEMD	Ensemble Empirical Mode Decomposition
EMD	Empirical Model Decomposition
EU	European Union
GA	Grant Agreement
GCN	Graph Convolutional Network
GDPR	General Data Protection Regulation
GoA	Grade of Automation
GRA	Gray Relation Analysis
GTFS	General Transit Feed Specification
KoM	Kick-off Meeting

Acronym	Meaning
KPI	Key Performance Indicator
LSTM	Long Short-Term Memory
ML	Machine Learning
OCC	Operations Control Centres
ResNet	Residual Network
RF	Random Forest
RNN	Recurrent Neural Network
SARIMA	Seasonal ARIMA
SHAP	SHapley Additive exPlanations
SIL	Safety Integrity Level
STARIMA	Space-Time ARIMA
SVM	Support Vector Machine
TCMS	Train Control and Monitoring System
UITP	Union Internationale des Transports Publics
VEMS	Vehicle Equipment Maintenance System
WGAN	Wasserstein Generative Adversarial Network
WNN	Wavelet Neural Network
WP	Work Package
XAI	Explainable AI
YOLO	You Only Look Once

1 INTRODUCTION

1.1 NEXUS PROJECT

The project **Next-gen technologies for enhanced metro operation** (NEXUS) is a Horizon Europe project running from 1 October 2024 to 30 September 2026 and deployed by a consortium of 13 partners. The objective of the NEXUS project is to establish an innovative benchmark, addressing crucial challenges and guiding European metros toward transformative futures. Through optimization, analysis, energy and service efficiency, NEXUS aspires to pioneer innovative solutions in 2 European cities (Genoa, Italy and Sofia, Bulgaria) for the urban and metro transport of the future.

1.2 PURPOSE OF THE DELIVERABLE

The integration of **AI, IoT, and Big Data** is poised to revolutionize metro systems, transforming urban transportation into a more intelligent, efficient, and sustainable mode of mobility. These technologies will drive automation, optimize operational workflows, and enhance real-time decision-making, creating safer, more reliable, and seamlessly connected metro networks. By harnessing the power of **AI-driven analytics**, **IoT-enabled connectivity**, and **Big Data insights**, metro systems can not only improve operational efficiency but also offer enhanced safety, sustainability, and a better experience for passengers.

This document marks the first deliverable of **Work Package 6 (WP6)** and presents the findings of **Task 6.1**, titled "*Deep Dive – Data Science and AI in Future Metro Operations*." It provides a thorough review of the current landscape of **AI, IoT, and Big Data** applications within the context of future metro operations. As the transportation sector faces increasing demands for smarter, more adaptable infrastructure, understanding how AI and data science can drive metro systems forward is crucial. The deliverable aims to provide readers with the foundational knowledge necessary to understand the transformative potential of these technologies and their real-world applications.

The primary goal of this deliverable is to equip readers with key insights into future metro operations, specifically focusing on how **AI** and **data science** can be leveraged to enhance system performance. It explores relevant use cases and offers practical implementation guidelines to support the integration of these cutting-edge technologies into metro networks. Additionally, the document outlines the **data science and AI demonstrators** that will be developed and delivered throughout the project, setting the stage for tangible outcomes that can be applied in real-world metro systems.

1.3 STRUCTURE OF THE DELIVERABLE

This deliverable is structured as follows:

- Section 2 explores the foundations of (1) data science, (2) machine learning (ML), and AI, as well as (3) metro operations and outlines a section on European's approach on implementing AI solutions.

- Section 3 presents the state of the art and emerging trends in AI and data science for future metro systems, based on studies conducted by industry experts and analysts in the transportation sector, along with a comprehensive list of key use cases.
- Section 4 presents a deep dive for selected AI use cases on future metro operations, expanding the list of identified use cases and defining the scope for the demonstrator applications within the WP.
- Section 5 presents a more in-depth examination of NEXUS AI use cases, providing insights into their technical aspects and potential challenges for future implementation.
- Section 6 discusses best practices in line with industrial standards for metro operations, ensuring that the integration of these technologies is aligned with the highest operational standards.

2 FOUNDATIONS

2.1 DATA SCIENCE

The widespread adoption of digital technologies, both across various sectors and specifically within metro operations, generates vast amounts of data that can be leveraged to significantly enhance operational efficiency and overall performance. When properly analysed, this data becomes a valuable resource, enabling better decision-making and the optimization of metro system operations.

Data science is an interdisciplinary field that merges principles from mathematics, statistics, AI, and computer engineering to analyse (large) datasets and extract meaningful insights. It applies scientific methods, processes, algorithms, and systems to interpret real-world phenomena through data, while also integrating domain expertise from fields like natural sciences, information technology, and mobility and transport.

As a discipline, data science is focused on developing innovative approaches and methodologies, which are validated through the analysis of real-world data. It emphasizes the extraction of actionable insights from both structured and unstructured data sources, addressing complex challenges encountered in dynamic, large-scale environments. This is especially relevant in the context of mobility and transport, where the volume of data generated by sensors, vehicles, infrastructure, and passengers requires advanced analytical techniques.

For future metro systems, data science enables the integration of these diverse data streams to enhance predictive analytics, optimize resource allocation, and increase system reliability. Moreover, the insights derived from these analyses can drive innovations in passenger experience, safety measures, and environmental sustainability. By fully leveraging the power of data science, metro systems can evolve into more adaptive, efficient, and responsive entities that better meet the needs of both passengers and operators alike.

Recent research has introduced terms such as urban analytics (e.g., Batty, 2019; Kand & Batty, 2019), transport data science, and mobility data science (e.g., Mokbel et al., 2023; Mokbel et al., 2022; Stocker et al., 2024) to highlight the synergies between data science and the mobility and transport domains. These concepts underscore the growing potential to apply advanced data analysis techniques to optimize urban mobility systems, as well as to enhance transportation planning, management, and decision-making.

In general, data science projects follow a straightforward process, as illustrated in the Figure 1 below, beginning with data import (ingestion) and culminating in the communication of results.

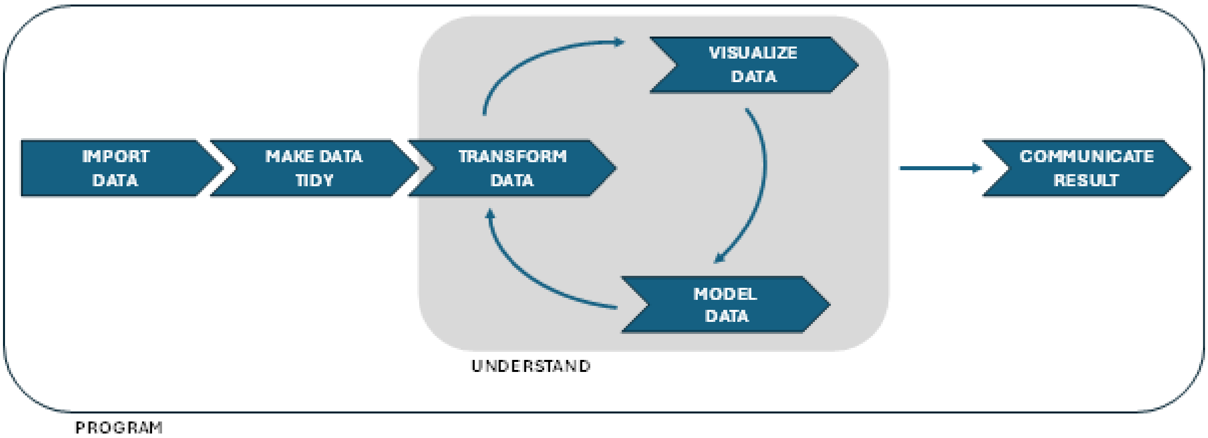

Figure 1: Data Science Process (Source: Hadley et al. 2023)

In the first step, the data provided (e.g., by metro operators) must be imported into an analysis tool. The next step involves transforming this data into a "tidy" format, where each column represents a variable, and each row represents an observation. This "tidy" format makes it easier to address questions from the use cases effectively. After discussions with use case partners have provided a rough idea of the data analysis approach, the data must be further transformed into an appropriate analytical structure. This includes tasks like combining tables, filtering and selecting data, and performing calculations. Additionally, focusing the data on particularly relevant areas is crucial. New variables are created, and summary statistics are calculated to gain a deeper understanding of the data. Once the direction of the analysis is defined, two essential tools help to develop a clearer understanding: visualization and modelling. Effective visualizations can uncover unexpected patterns and relationships, prompting new questions or indicating the need for more data. Models serve as complementary tools to exploratory visualizations. Once the questions to be answered are clearly defined, models can be built to address them. Finally, the results are communicated to stakeholders, and the findings are validated against their expectations.

Based on data science processes, such as those introduced by Pfister and Blitzstein (2016) from Harvard University, or other process models like CRISP-DM (Chapman et al. 1999), Mobility Data Science suggests a framework for generating data-driven applications ("digital mobility services"), as illustrated in the Figure 2 below. This approach typically involves the five steps (1) asking questions, (2) collecting data, (3) examining data, (4) modelling data, and (5) communicating results. A Mobility Data Science framework (Stocker et al., 2024) provides a structure for developing data-driven products for future metro systems. It consists of three key building blocks: mobility and transport artifacts (e.g., passengers, trains, train stations), the mobility data science approach (the process methodology), and digitized mobility services (the applications).

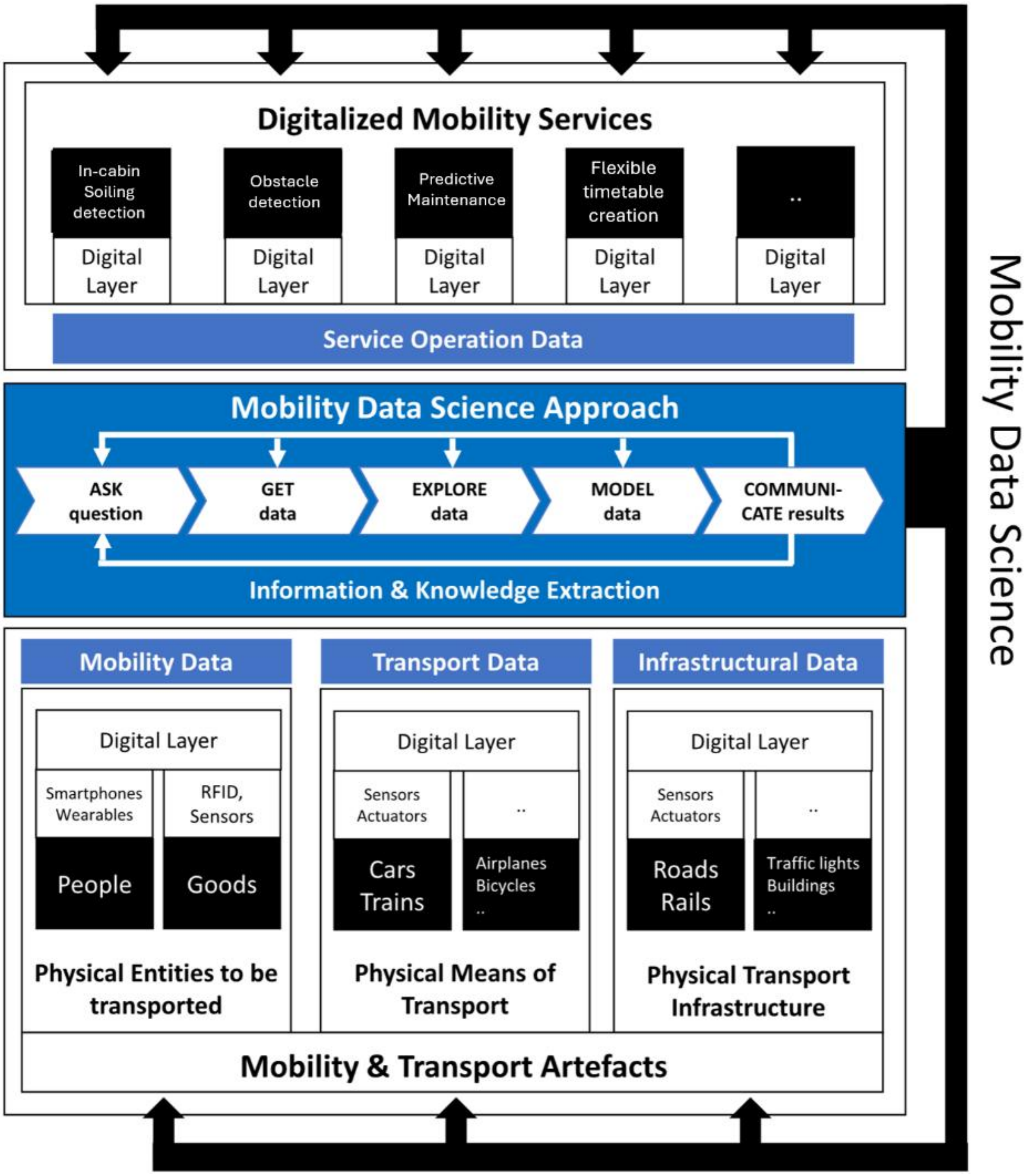

Figure 2: Mobility Data Science Process (Source: Stocker et al. 2024)

Mobility and transport artifacts generate vast amounts of data. For instance, passengers generate data directly by purchasing tickets or moving through stations (via their smartphones), or indirectly through monitoring systems such as cameras or by entering and exiting gates. The data collected from passengers not only provides insights into individual movement patterns but also allows metro operators to anticipate traffic flow, improve station management, and optimize passenger services. Trains produce substantial data during their operation, which is captured both in static timetables and dynamically through the monitoring of their behaviour, such as location, speed, delays, and energy consumption. This dynamic data provides real-time insights into train performance, enabling predictive maintenance, route optimization, and overall service reliability. The infrastructure, including tracks, metro stations, and other facilities, also generates data through sensors or cameras. For example, sensors can detect wear and tear on tracks, monitor air quality in stations, or assess passenger traffic within the system. This comprehensive data collection across multiple sources offers a detailed and real-time picture of the entire metro ecosystem.

This data feeds into algorithms, which are a critical component of the data science approach, spanning from formulating questions to communicating results. Algorithms process and analyse the data to uncover hidden patterns, make predictions, and guide decision-making processes. By leveraging these insights, metro systems can improve operational efficiency, enhance safety, and provide a better overall experience for passengers.

The insights extracted from this data are then utilized for digital mobility services (data-based applications) to improve future metro service operations, facilitating innovative applications such as in-cabin soling detection, which enhances passenger safety by detecting and alerting operators about unwanted objects or conditions, or flexible timetable creation and optimization using GTFS (General Transit Feed Specification) data. The integration of dynamic scheduling and passenger demand patterns allows metro systems to adjust their services in real-time, improving efficiency and reducing congestion.

AI and ML play pivotal roles in the field of data science, enabling the analysis of large, complex datasets and the automation of decision-making processes. AI encompasses a range of technologies designed to simulate human intelligence and problem-solving abilities, while ML allows systems to learn from data and improve over time. Together, they enhance the capabilities of traditional data analysis methods, enabling more accurate predictions, identifying new trends, and optimizing operational decision-making.

2.2 MACHINE LEARNING (ML) AND ARTIFICIAL INTELLIGENCE (AI)

2.2.1 OVERVIEW

ML and AI revolutionized how complex systems are modelled and analysed. Thanks to their ability to analyse large sets of data, ML models and AI can recognize complex patterns, analyse processes, optimize decisions, and improve systems efficiency.

AI describes computer systems' ability to perform tasks that normally require human intelligence. These include learning, reasoning, solving problems, understanding the surrounding environment, and making decisions. AI is a computer science research area focused on developing and examining technologies that allow machines to sense their surroundings, apply intelligence and learning, and take appropriate actions to successfully reach specific objectives (Russell & Norvig, 2020). ML is a subset of AI that uses algorithms to analyse and uncover the patterns and relationships within data and information (Awad & Khanna, 2015).

ML and AI techniques do not require any a-priori knowledge of the system as it learns the relationship between input and output directly from the available data, for these reasons they are considered data-driven. The development (i.e., learning phase) of a data-driven model typically demands a substantial amount of historical data and significant computational resources. Conversely, the prediction phase (i.e., forward phase) is often computationally efficient. Although these models tend to achieve high overall accuracy, they may occasionally generate physically unrealistic predictions under certain conditions.

To generate predictions, ML algorithms construct a mathematical model capable of recognizing these patterns. Specifically, ML algorithms can adopt three primary learning approaches:

- **Supervised Learning**: This method utilizes labelled input data (i.e., training data) to teach models how to achieve the desired output (Hastie, Tibshirani, & Friedman, 2009). The training dataset includes both inputs and correct outputs, allowing the model to learn over time. The process continues until the model reaches a satisfactory level of accuracy on the training data.
- **Unsupervised Learning**: In this approach, models work with unlabelled input data, meaning no predefined labels are assigned to the samples (Ghahramani, 2003). The model attempts to identify hidden structures and patterns within the dataset without external guidance, grouping data based on similarities and representing it in a compressed format. Common applications include clustering, dimensionality reduction, and association rule learning, such as the A-priori algorithm and k-means clustering.
- **Semi-supervised Learning**: This technique leverages datasets that contain a small portion of labelled data alongside a large volume of unlabelled data (Zhu & Goldberg, 2009). The model aims to achieve the desired output while also learning the underlying structures to better organize the data. Semi-supervised learning algorithms extend other flexible methods by making assumptions about how to handle unlabelled data, such as the continuity assumption and cluster assumption.

Classification and regression (Shalev-Shwartz & Ben-David, 2014) are the two primary predictive problems that can be approached using supervised, unsupervised, or semi-supervised methods (Zaki & Meira Jr, 2019). The key distinction between classification and regression lies in what the model is designed to predict: classification focuses on assigning a label, while regression involves predicting a numerical value.

More specifically, **classification** is the process of approximating a mapping function that links input variables to discrete output categories (i.e., labels or classes). In this case, the model determines which class an observation belongs to, with no concept of distance between categories.

2.2.2 ALGORITHMS

Beyond learning styles and the types of problems they address, ML algorithms can also be categorized based on their underlying principles and operational similarities. The following list groups algorithms according to how they function:

Regression Algorithms: These algorithms operate by identifying relationships between variables (Chatterjee & Hadi, 2015). Such relationships are represented through an equation or model that links the dependent variable (i.e., response) to one or more independent variables (i.e., predictors). The model is then iteratively improved by minimizing the error in its predictions (Menard, 2002; Weisberg, 2005). Some of the most used regression algorithms include:

- Linear Regression;
- Logistic Regression;
- Ordinary Least Squares Regression;
- Stepwise Regression;
- Multivariate Adaptive Regression Splines.

Regularization Algorithms: Regularization is an ML technique, primarily used in regression algorithms, that helps control model complexity by reducing the magnitude of feature coefficients (Argyriou, Evgeniou, & Pontil, 2008; Evgeniou & Pontil, 2007). Simplifying the model mitigates the risk of overfitting, while shrinking the coefficients also reduces computational costs (Menard, 2002). Some of the most widely used regularization algorithms include:

- (Kernelized) Ridge Regression;
- Least Absolute Shrinkage and Selection Operator;
- Elastic Net;
- Least-Angle Regression.

Decision Tree Algorithms: These algorithms utilize a decision tree as a predictive model (Rokach & Maimon, 2007). In this structure, the branches represent observations about an item, while the leaves indicate the item's target value (Larose & Larose, 2014). Decision tree algorithms can be applied to both classification and regression problems (Safavian & Landgrebe, 1991). One of their key advantages is their high interpretability (Molnar, 2020). Some of the most widely used decision tree algorithms include:

- Classification Trees;
- Regression Trees;
- Iterative Dichotomiser 3;
- Chi-squared Automatic Interaction Detection;
- Decision Stump;
- Conditional Decision Trees.

Instance-based Algorithms: These algorithms make predictions by comparing new instances with previously stored training instances (Daelemans, Van den Bosch, & others, 2005). They build a database of example data, which is then used to find similarities and make predictions (Russell & Norvig, 2003). Due to this approach, they are also referred to as memory-based learning. Some of the most used instance-based algorithms include:

- k-Nearest Neighbour;
- Learning Vector Quantization;
- Locally Weighted Learning;
- Self-Organizing Maps.

Clustering Algorithms: Clustering involves dividing a dataset into multiple groups, ensuring that data points within the same group are more similar to each other than to those in different groups (Gan, Ma, & Wu, 2020). These algorithms are commonly used in unsupervised learning, as they focus on identifying structures within unlabelled data (Berkhin, 2006). Some of the most widely used clustering algorithms include:

- Hierarchical Clustering;
- K-Means;
- K-Medians;
- Expectation Maximization;
- Spectral Clustering.

Bayesian Algorithms: These algorithms construct ML models based on Bayes' Theorem (Barber, 2012). Their primary objective is to estimate the posterior distribution using the likelihood and prior distribution (Rasmussen, 2003). Some of the most used Bayesian algorithms include:

- Naive Bayes;
- Gaussian Naive Bayes;
- Multinomial Naive Bayes;
- Averaged One-Dependence Estimators;
- Bayesian Network;
- Bayesian Belief Network.

Artificial Neural Network Algorithms: This category includes algorithms inspired by the biological neural networks found in animal brains (Amari & others, 2003; Bishop & others, 1995). Artificial neural networks can be applied to both classification and regression tasks, but they also form a vast subfield with numerous algorithms and variations (Yegnanarayana, 2009). Some of the most widely used neural network algorithms include:

- Hopfield Networks;
- Radial Basis Function Networks;
- Perceptron Back-Propagation.

Deep Learning Algorithms: This category includes artificial neural network algorithms, but unlike standard neural networks, the term "deep" refers to the presence of multiple layers within the network (LeCun, Bengio, & Hinton, 2015; Ngiam, et al., 2011). Deep learning algorithms operate on significantly larger and more complex neural architectures (Schmidhuber, 2015). Some of the most widely used deep learning algorithms include:

- Deep Boltzmann Machine;
- Convolutional Neural Networks;
- Deep Belief Networks;
- Stacked Auto-Encoders.

Association Rule Learning Algorithms: These algorithms are primarily used to identify meaningful relationships between variables in large databases (Zhang & Zhang, 2003). More specifically, their objective is to discover strong rules within datasets by leveraging various interestingness measures (Al-

Maolegi & Arkok, 2014; Zheng, Kohavi, & Mason, 2001). The three most widely used association rule learning algorithms are:

- A-priori Algorithm;
- Eclat Algorithm;
- FP-growth Algorithm.

Ensemble Algorithms: These algorithms focus on combining predictions from multiple weaker ML models to achieve more robust and accurate results (Bühlmann, 2012). Each model is trained independently, and their outputs are then aggregated to generate the final prediction (Dietterich, 2000; Zhang & Zhang, 2003). The key challenge lies in selecting the appropriate models and determining the best way to combine them. Some of the most commonly used and powerful ensemble algorithms include:

- Random Forest;
- Gradient Boosted Regression Trees;
- Boosting;
- AdaBoost;
- Bagging;
- Gradient Boosting Machines.

Dimensionality Reduction Algorithms: These algorithms leverage the underlying structure of data to transition from a high-dimensional space to a lower-dimensional one while retaining essential properties of the original data (Sorzano, Vargas, & Montano, 2014; Van Der Maaten, Postma, Van den Herik, & others, 2009). They can be applied to both classification and regression problems. Some of the most commonly used dimensionality reduction algorithms include:

- Principal Component Regression;
- Linear Discriminant Analysis;
- Quadratic Discriminant Analysis;
- Mixture Discriminant Analysis;
- Flexible Discriminant Analysis;
- Principal Component Analysis;
- Sammon Mapping.

Novelty/Outlier/Anomaly Detection Algorithms: These algorithms focus on identifying new or unknown data that an ML system has not encountered during training (Miljković, 2010). Specifically, they detect outliers that deviate from the normal data distribution. Novelty detection is a critical challenge in classification systems and one of the most complex problems in ML, as it depends on the statistical properties of previously known information (Markou & Singh, 2003; Pimentel, Clifton, Clifton, & Tarassenko, 2014). Some of the most widely used novelty detection algorithms include:

- k-Nearest Neighbour Data Description;
- k-Nearest Neighbour Outlier Detection;
- Local Outlier Factor;
- Angle-Based Outlier Detection;
- Support Vector Data Description;

- Gaussian Data Description;
- Parzen Window Data Description;
- Local Correlation Integral.

2.3 EUROPE'S PERSPECTIVE ON AI AND DATA-BASED APPLICATIONS

Europe is taking a proactive and principled approach to artificial intelligence, seeking to balance innovation with fundamental rights and safety. The cornerstone of this effort is the **EU AI Act** (European Commission 2024; European Parliament 2024), the world's first comprehensive regulation on AI, which classifies systems by **risk level**—from minimal to unacceptable.

The purpose of the AI Act is to strengthen the internal market and encourage the development and adoption of human-centric, trustworthy artificial intelligence. At the same time, it aims to ensure a high level of protection for health, safety, fundamental rights—including those outlined in the EU Charter—democracy, the rule of law, and the environment, by addressing potential risks associated with AI systems, while also fostering innovation. The Regulation sets out consistent rules across the EU for placing and using AI systems on the market, including restrictions on certain unacceptable practices and detailed requirements for high-risk systems. It also introduces transparency obligations, governance and enforcement mechanisms, and specific provisions for general-purpose AI models. To foster innovation, the Regulation includes supportive measures, especially for small and medium-sized enterprises and startups.

Article 3 of the AI Act defines an AI system as:

"AI system' means a machine-based system that is designed to operate with varying levels of autonomy and that may exhibit adaptiveness after deployment, and that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments"

Given the broad scope of the EU AI Act's definition, regulatory obligations are not solely determined by how AI is built, but rather by its intended use. This usage-based approach reflects the Act's risk-based framework, where obligations increase with the potential impact on fundamental rights and safety. The European Law Institute (2024) offers a thoughtful and comprehensive response to the AI Act, highlighting both the strengths of this framework in promoting trustworthy AI and the challenges in its practical implementation across diverse sectors.

Certain AI uses, like government-run social scoring, are outright prohibited for being incompatible with EU values. The EU AI Act bans all AI systems that pose a clear threat to the safety, livelihoods, and rights of individuals. It specifically prohibits eight practices, including harmful AI-based manipulation and deception, exploitation of vulnerabilities, social scoring, criminal offense risk prediction, untargeted scraping of internet or Closed-Circuit Television (CCTV) material to expand facial recognition databases, emotion recognition in workplaces and educational institutions, biometric categorization to deduce protected characteristics, and real-time remote biometric identification for law enforcement in public spaces.

AI use cases that can pose serious risks to health, safety or fundamental rights are classified as high-risk. These high-risk use-cases include:

- AI in critical infrastructure (e.g., transportation) that could threaten public health and safety.
- AI in education systems affecting access to education and career progression (e.g., exam scoring).
- AI safety components in products (e.g., robot-assisted surgery).
- AI tools for employment, worker management, and self-employment (e.g., CV sorting for recruitment).
- AI used in providing essential services (e.g., credit scoring affecting loan access).
- AI systems for remote biometric identification, emotion recognition, and categorization (e.g., identifying shoplifters).
- AI in law enforcement that could impact fundamental rights (e.g., evaluating evidence reliability).
- AI in migration, asylum, and border control (e.g., visa application assessments).
- AI in justice and democracy administration (e.g., preparing court rulings).

High-risk AI systems must meet strict obligations before entering the market, including:

- Comprehensive risk assessment and mitigation strategies.
- High-quality datasets to minimize discriminatory outcomes.
- Activity logging for traceability.
- Detailed documentation for compliance assessment by authorities.
- Clear information for system deployers.
- Adequate human oversight measures.
- Robustness, cybersecurity, and accuracy standards.

High-risk AI applications—such as those in transportation and critical infrastructure—must comply with strict requirements for transparency, accountability, data governance, and human oversight. The EU's framework promotes trustworthy AI, balancing innovation with the protection of fundamental rights. For railway and metro operators, this means that while many AI systems may be classified as minimal or limited risk, applications related to operational safety, predictive maintenance, surveillance, or workforce management are likely to fall into the high-risk category. These systems must therefore meet rigorous compliance standards under the AI Act.

2.4 METRO OPERATIONS

Metro operations encompass the systematic management and coordination of metro rail systems, which are crucial for maintaining continuous and efficient operations (Zhao et al., 2017). This encompasses a range of activities and components aimed at ensuring the safe movement of passengers and the seamless functioning of urban rail systems (Mehta et al., 2019).

The efficiency and effectiveness of metro operations depend on a wide range of internal and external factors (Lobo & Couto, 2016; Mehta et al., 2019; Shahabi et al., 2021; Zhao et al., 2017). These internal and external factors are frequently referred to as the "foundations" of metro operations. They encompass the fundamental elements and principles that underpin the efficient and effective functioning of metro systems. Summarizing and categorizing the findings of a comprehensive literature analysis investigating internal and external factors influencing metro operations conducted by Lobo and Couto (2016), these foundations include the following internal and external factors:

- **Socio- and Macroeconomic Factors:** These include area, population density, average household size, unemployment rate, GDP per capita, and diesel pump price. These factors influence urban socioeconomic trends, which in turn affect metro operations.
- **Policies:** The development of policies and actions aimed at promoting sustainability in urban transit, such as network expansions, fare subsidies, and the regulation of private car use, can either increase or decrease the demand for metro services.
- **Internal Production Factors:** Key factors such as network length, number of stations, number of cars, and number of employees significantly impact the operations required to maintain metro services. These factors encompass both capital and labour inputs, whether available or desired.
- **Efficiency and Effectiveness:** This involves the technical efficiency of the production process and the effectiveness in attracting users and meeting demand.

As evidenced by the internal and external factors influencing metro systems and highlighted by several studies such as those by Castagna et al. (2024) and Mehta et al. (2019), each metro system has distinct requirements and necessitates different solutions. Consequently, metro operations must be adapted to the specific conditions relevant to their context to ensure operational efficiency. Nevertheless, research analyses conducted by *Zhao et al. (2017) and* Mehta et al. (2019) identified several key elements that metro systems must fulfil to collectively contribute to their efficient and effective functioning. These foundational elements work together to create a reliable, efficient, and user-friendly metro system that meets the transportation needs of urban populations. These key elements include, but are not limited to:

- **Service Delivery and Timetabling:** Scheduling and running trains to meet passenger demand. Ensuring timely and reliable service. Maintaining regular intervals between trains and minimizing waiting times.
- **Operations Control Centres (OCC):** Command and control facilities for monitoring and managing the metro system. Coordinating normal and emergency operations. Making real-time decisions to maintain service continuity.
- **Maintenance and Infrastructure Management:** Regular and preventive maintenance of trains, tracks, signalling systems, and infrastructure. Upgrading physical assets to ensure safety and reliability. Preventing disruptions and maintaining overall system quality
- **Safety and Security:** Implementing measures to protect passengers and staff. Surveillance, emergency response plans, and safety protocols
- **Customer Service:** Providing assistance to passengers. Handling inquiries. Ensuring a positive travel experience.
- **Revenue Management:** Managing ticket sales, fare collection, and financial transactions. Optimizing income and reducing losses.

- **Platform Assignment and Capacity Management:** Allocating platforms for arriving and departing trains. Optimizing passenger flow and reducing congestion. Ensuring the system can handle expected passenger volume without overcrowding or underutilization. Planning for peak hours and adjusting services to meet demand.
- **Traffic and Passenger Flow Management:** Monitoring and controlling the movement of trains and passengers. Preventing congestion and ensuring smooth operations. Using traffic management systems and real-time monitoring tools to reduce congestion and optimize system performance.
- **Energy Efficiency:** Minimizing energy consumption through optimized train trajectories and timetables. Reducing operational costs and environmental impact.
- **Operational Research Techniques:** Applying advanced algorithmic techniques and models. Optimizing timetabling, platform assignments, and crew scheduling.
- **Staff Training and Management:** Training and managing the workforce. Including train operators, maintenance crews, and customer service personnel.

3 AI IN METRO OPERATIONS

3.1 METRO OPERATIONS & AI: REPORTS

This chapter presents a summary of desktop research conducted on the application of AI in metro operations. While the majority of studies and articles reviewed focus broadly on railway operations—including metro systems—or on public transport more generally, many of the identified use cases and insights are highly relevant and applicable to NEXUS.

Particularly noteworthy are three reports that provide valuable perspectives:

- A knowledge brief from the International Association of Public Transport (UITP) on AI use cases "*AI in Public Transport. How to use AI in urban mobility"* (UITP 2025),
- A report from the International Association of Public Transport (UITP) on AI use cases **"**Artificial Intelligence in mass public transport" (UITP 2018), and
- A comprehensive analysis by McKinsey & Company in collaboration with the International Union of Railways (UIC) "The journey towards AI-enabled railway companies" (McKinsey and UIC. 2024).

This section provides a summary of the UITP Knowledge Brief on Artificial Intelligence in public transport.

3.1.1 ARTIFICIAL INTELLIGENCE IN PUBLIC TRANSPORT (UITP REPORT)

The UITP Knowledge Brief offers an updated overview of AI applications in public transport for 2025, building on the foundational insights of the UITP's 2017 report. This updated brief reflects the significant evolution of AI technologies and their growing integration into transport operations, with a focus on real-world implementations shown though short case studies in the report.

The brief outlines the **primary uses of AI in public transport today**, which focus largely on enhancing operational efficiency through **data analysis**, **anomaly detection**, and **predictive maintenance**. These applications help transport operators make more informed decisions, anticipate equipment failures, and optimize performance.

It also highlights three key technological categories of AI applications that are shaping the sector:

- Large Language Models (LLMs) – primarily used to power chatbots and virtual assistants, improving customer service through natural language processing and multilingual support.
- AI-Driven Video Analytics – leveraging advanced image processing for applications such as crowd monitoring, behavioural analysis, and safety management.
- Predictive Modelling – applied to forecast and address operational challenges, from passenger flow patterns to infrastructure wear and tear.

The UITP Knowledge Brief highlights a series **of LLM-based use cases**. For **customer assistance**, LLMs are helping in a few keyways:

- Text-to-speech engines are used to deliver clear spoken information to passengers.

- Digital sign language avatars convert text and spoken announcements into sign language and multiple written languages, helping passengers with hearing loss.
- Chatbots are used to answer simple, common questions about public transport services. Some of these chatbots use a technique called retrieval-augmented generation (RAG), which makes their responses more accurate and useful. They also allow passengers to report incidents in real time.

For **staff support**, LLMs are also being used:

- Frontline workers can use AI-powered chatbots to submit support requests more easily.
- Customer service centres are testing generative AI to improve chatbot functions and better support passenger inquiries.

The UITP Knowledge Brief further highlights a range of **AI-powered video analytics** use cases in public transport, focused on improving safety, efficiency, and accessibility.

- **Safety and Driver Assistance**: This use case involves advanced driver assistance systems on buses. It includes features like driver fatigue monitoring, blind spot detection, and a high-capacity surveillance system. It also supports real-time seat availability displays that show upper-deck occupancy levels to passengers.
- **Railroad Crossing Safety and Intrusion Detection**: AI video analytics help improve safety at railroad crossings by detecting trespassing and tunnel intrusions. The system flags violations and generates video clips of incidents for detailed review and enforcement.
- **Occupancy Monitoring**: This use case uses real-time video from existing onboard cameras to estimate how full a bus is. The system classifies occupancy into five levels to help operators manage service levels and inform passengers.
- **Bus Lane and Parking Enforcement**: AI-powered cameras monitor bus stops and bus-only lanes. When a vehicle is parked illegally, the system records a 10-second video, captures the license plate, and sends the footage—along with the time and location—to parking enforcement.
- **Fare Evasion Detection and Enforcement**: Cameras at major urban stations are used to detect fare evasion. The system supports ticket inspectors with a mobile app that helps them identify and respond to fare evaders more effectively.
- **Guidance for Blind and Visually Impaired Users:** A smartphone app uses video analytics to help visually impaired passengers locate nearby bus stops. It uses the phone's camera and AI trained on a small image set to guide users to the correct location within the camera's field of view.

The UITP Knowledge Brief outlines several use cases where **predictive modelling with AI** is being applied.

- **AI for Driver Efficiency**: This use case involves analysing on-vehicle telemetry data along with external factors like traffic, passenger load, and weather. AI is used to understand driving styles under different conditions, identify high-risk zones, detect recurring behaviors that may need attention, and support targeted driver training sessions.
- **Smart Charging in E-Bus Fleets**: AI helps optimize when and how electric buses are charged. This system adjusts the charging schedule dynamically, ensuring it doesn't disrupt operations while taking advantage of lower energy prices during off-peak hours.
- **Accurate Arrival Time Predictions**: In this use case, AI and machine learning (ML) are used to predict vehicle arrival times with higher accuracy. These predictions can improve service reliability and passenger communication.

- **AI-Based Mobility Forecasts**: This approach involves developing traffic models based on individual travel behaviour. These models are combined with real-time data to provide more precise and responsive forecasts of demand and traffic conditions.
- **AI-Controlled Metro Ventilation**: Ventilation in metro systems is essential for passenger comfort and air quality. In this use case, AI selects the best ventilation strategy in real time, based on factors like weather conditions, indoor and outdoor air quality, energy use, fan performance, and energy prices.

The UITP Knowledge Brief highlights several key performance improvements driven by AI in different use cases across public transport operations. One of the notable achievements is a 13% increase in prediction accuracy for modelling demand and arrival times. his improvement enhances the reliability of service schedules and allows for better planning, benefiting both operators and passengers. Additionally, AI-powered driving assistance and training **have resulted in a** 40% reduction in improper vehicle use. By identifying risky driving behaviors and offering targeted training, AI is helping to enhance driver efficiency and safety.

Table 1: AI Use Cases (Source: UITP 2025)

AI APPLICATION	USE CASE	DESCRIPTION
Large Language Models (LLMs)	Pattern recognition for track conditions	Deliver spoken information for better accessibility.
Network capacity maximization	Real-time condition monitoring	Convert text and spoken announcements into sign language and written languages.
Large Language Models (LLMs)	Chatbots for customer assistance	Answer simple queries and allow real-time incident reporting.
Large Language Models (LLMs)	AI-powered chatbots for staff support	Allow frontline workers to submit support requests efficiently.
Large Language Models (LLMs)	Generative AI for customer service	Enhances chatbot functions to improve passenger inquiry handling.
AI-Driven Video Analytics	Safety and Driver Assistance	Monitors driver fatigue, blind spots, and provides seat availability in real-time.
AI-Driven Video Analytics	Railroad Crossing Safety and Intrusion Detection	Detects trespassing and tunnel intrusions for better safety management.
AI-Driven Video Analytics	Occupancy Monitoring	Estimates bus occupancy to manage service levels.
AI-Driven Video Analytics	Bus Lane and Parking Enforcement	Monitors illegal parking, captures license plates, and sends data to enforcement.
AI-Driven Video Analytics	Fare Evasion Detection	Monitors stations and supports ticket inspectors to identify fare evaders.

AI APPLICATION	USE CASE	DESCRIPTION
AI-Driven Video Analytics	Guidance for Blind and Visually Impaired Users	Guides visually impaired passengers to bus stops using smartphones and AI.
Predictive Modelling	Driver Efficiency	Analyses driving styles using telemetry data to improve safety and training.
Predictive Modelling	Smart Charging in E-Bus Fleets	Optimizes e-bus charging during off-peak hours to reduce energy costs.
Predictive Modelling	Accurate Arrival Time Predictions	Uses AI/ML to predict vehicle arrival times more accurately.
Predictive Modelling	AI-Based Mobility Forecasts	Combines real-time data with individual travel behaviour to forecast mobility demand.
Predictive Modelling	AI-Controlled Metro Ventilation	Adjusts metro ventilation based on weather, air quality, and energy use for improved passenger comfort.

3.1.2 ARTIFICIAL INTELLIGENCE IN MASS PUBLIC TRANSPORT (UITP REPORT)

The 2018 UITP Report on Artificial Intelligence in Mass Public Transportation (UITP 2018) highlights several key AI applications in the public transport sector. These applications include (1) real-time operations management, (2) customer analytics, (3) predictive maintenance, and (4) network planning and route design. Each of these areas is demonstrating the transformative potential of AI to improve efficiency, enhance customer experiences, and optimize service delivery.

Additionally, the report identifies five main challenges faced by public transport authorities in adopting AI. These challenges are:

- Improvement of data quality, ensuring that the data used by AI systems is accurate, reliable, and actionable.
- Building capacity and knowledge in AI deployment, to enable operators to effectively integrate AI solutions into existing systems.
- Overcoming data privacy concerns, ensuring that AI applications comply with regulations and protect passenger data.
- Meeting the requirements of data volume for AI, as AI systems often require large quantities of data to function optimally.
- Establishing commitment from top management for cultural and process changes, ensuring that AI adoption is supported at all levels of the organization.

The report also collected in-depth information on 17 AI use cases across four key areas in the public transport sector, demonstrating how AI is gaining traction and driving improvements.

AI for Customer Excellence

The AI for Customer Excellence category focuses on improving passenger experiences through innovative AI applications. One example is the MTR Chatbot, which assists passengers by answering inquiries and providing real-time updates about services. Similarly, TfL TravelBot is a chatbot used by Transport for London (TfL) to offer travel information and service updates to passengers. Another notable application is the JR East-Hitachi Communication Robot, a robot designed to help passengers with information and guidance at stations, improving accessibility and convenience. Additionally, the JR East-IBM Call Centre Support System uses AI to enhance customer support by improving response times and the efficiency of call centre operations.

AI for Operational Excellence

The AI for Operational Excellence category focuses on improving the efficiency of transport operations through advanced AI technologies. One application, the RTRI Predicting Method of Train Delay and Train Congestion, uses AI to predict delays and congestion, allowing for better management of train schedules. SBB Reinforcement Learning for Railway Dispatching applies reinforcement learning to optimize the dispatching of trains, improving operational efficiency. Similarly, NEC Predictive Optimization for Bus Operations uses AI to predict and optimize bus operations, enhancing route efficiency and scheduling.

In Shenzhen, the Shenzhen Bus Group-Haylion Technologies 'Alphaba' Intelligent Driving Public Bus Trial explores the use of AI-powered intelligent driving for buses, enhancing safety and efficiency. RATP Dev 'Interstellar' Mass Transit Data Analytics System is another example, using data analytics to optimize mass transit operations. Siemens Mobility Data Analytics for Mobility Demand Prediction uses AI to predict mobility demand and optimize public transport routes accordingly.

Further examples include the Axon Vibe-SBB Smart Travel Assistant and Travel Cockpit, which leverages AI to enhance passenger and operational management, and Alibaba ET City Brain, a smart city initiative using AI to manage urban transportation networks. Lastly, the LTA Automatic Traffic Monitoring on Drone Images system, implemented by the Land Transport Authority in Singapore, uses drones to monitor traffic and optimize traffic flow.

AI for Engineering Excellence

The AI for Engineering Excellence category focuses on improving infrastructure and engineering operations using AI. One example is the RTRI Automatic Tunnel Lining Crack Detection, which uses AI to detect cracks in tunnel linings, ensuring the integrity and safety of critical infrastructure. Another application is the Yutong Bus-Shanghai Bus Group Intelligent Charging Control System, which uses AI to manage and optimize the charging systems of electric buses, improving efficiency and reducing downtime.

AI for Safety and Security Management

The AI for Safety and Security Management category focuses on enhancing safety and security within public transport systems. One example is SMRT Buses 'ProLearn' Data Analytics and Accident Risk Prediction, which uses data analytics to predict and reduce the risk of accidents in bus operations, helping to improve overall safety. Another example is the AWAAIT-FGC 'Detector' Fraud Detection System, an AI-driven solution designed to detect and prevent fraud in fare collection, ensuring integrity and reducing financial losses.

Table 2: AI Use Cases (Source: UITP 2018)

AI APPLICATION	USE CASE	DESCRIPTION
AI for Customer Excellence	Chatbot	A chatbot assisting passengers with inquiries and providing real-time service updates.
AI for Customer Excellence	TravelBot	A chatbot offering travel information and service updates to passengers.
AI for Customer Excellence	Communication Robot	A robot designed to help passengers with information and guidance at stations.
AI for Customer Excellence	Call Centre Support	An AI-powered system that enhances customer support and improves call center response times.
AI for Operational Excellence	Predicting Train Delay and Congestion	AI predicts delays and congestion, improving train schedule management.
AI for Operational Excellence	Railway Dispatching	Reinforcement learning is applied to optimize the dispatching of trains, improving operational efficiency.
AI for Operational Excellence	Optimization for Bus Operations	AI predicts and optimizes bus operations, improving route efficiency and scheduling.
AI for Operational Excellence	Intelligent Driving Public Bus Trial	AI-powered intelligent driving trial for buses, enhancing safety and operational efficiency.
AI for Operational Excellence	Mass Transit Data Analytics System	A data analytics platform that optimizes mass transit operations.
AI for Operational Excellence	Mobility Demand Prediction	AI predicts mobility demand and optimizes transport routes.
AI for Operational Excellence	Travel Assistant and Travel Cockpit	AI-powered travel assistant and cockpit for improved passenger and operational management.
AI for Operational Excellence	City Brain	A smart city initiative using AI to optimize urban transportation networks.
AI for Operational Excellence	Traffic Monitoring on Drone Images	Drones are used to monitor traffic and optimize flow.
AI for Engineering Excellence	Tunnel Lining Crack Detection	AI detects cracks in tunnel linings, ensuring infrastructure integrity and safety.

AI APPLICATION	USE CASE	DESCRIPTION
AI for Engineering Excellence	Charging Control System	AI optimizes and manages charging systems for electric buses, improving efficiency and reducing downtime.
AI for Safety and Security Management	Data Analytics and Accident Risk Prediction	AI-driven data analytics to predict and reduce accident risk in bus operations.
AI for Safety and Security Management	Fraud Detection System	AI system for detecting and preventing fraud in fare collection, improving financial integrity and reducing losses.

The UITP report further highlights **AI-driven innovations of the future**, (1) smart station, (2) customer sentiment tracking, (3) mobility health tracker for public transport, (4) customer data engine, (5) incident disruption and simulation, and (6) smart grid for urban mobility.

3.1.3 THE JOURNEY TOWARD AI-ENABLED RAILWAY COMPANIES (MCKINSEY AND UIC 2024)

This report examines how AI, including generative AI, is being integrated into the railway sector, with a focus on existing and scalable future applications. The scope is limited to machine learning and deep learning, intentionally excluding robotics to concentrate on data-driven technologies.

Traditionally, the rail industry has been cautious in adopting digital innovations. Insights from participating railway companies suggest this hesitation stems from several challenges. Chief among them are difficulties accessing high-quality, well-organized data, often fragmented across siloed systems that hinder scalable AI development. Regulatory complexities—such as ambiguities around data ownership, permissible uses, and compliance—further complicate progress. The lack of industry-wide standards and low digital maturity have made it even harder to implement AI solutions effectively. Additionally, concerns persist about losing critical skills and institutional knowledge as AI transforms traditional work practices.

Despite these obstacles, the industry is beginning to evolve. Notable progress includes the introduction of more digitally connected assets, such as modern rolling stock, and the faster rollout of data-driven applications, enabled by low-code and no-code development platforms. AI initiatives to date have largely focused on strategic priorities: boosting punctuality, improving passenger services, enhancing safety, and streamlining operations. However, few companies have successfully scaled these applications. Moving forward, the successful adoption of AI across the sector will depend heavily on strengthening data governance and ensuring robust cybersecurity measures.

The McKinsey/UIC report identifies significant potential for AI to enhance a wide range of business functions across the rail value chain. These are grouped into three main categories. First, **railway undertakings**, which include both direct and supporting activities involved in delivering the core rail service. This encompasses operations and crew scheduling, disruption and incident management, rolling stock maintenance, station operations, rolling stock procurement and inventory management, crew training, onboard services, and safety management. Second, **infrastructure management**, which covers the foundational systems that support rail service delivery. Key areas include network planning and optimization, slot allocation and traffic control, maintenance, procurement and inventory management, infrastructure safety, stakeholder coordination, and infrastructure development and investment. Third, **passenger experience**, which focuses on customer-facing activities such as marketing and pricing strategies, booking and ticketing services, real-time passenger information, in-station revenue opportunities, and customer service.

The McKinsey/UIC report emphasizes that the AI use cases explored within the rail industry are closely aligned with four key performance indicators: on-time performance, customer engagement, safety, and operational efficiency. These KPIs reflect the primary goals driving AI adoption across the sector.

The report identifies **approximately 20 AI use cases** currently being explored or implemented by railway companies, each at varying levels of maturity. These use cases are illustrated in the Figure 3 below from the report, showcasing the breadth and depth of AI applications across the industry.

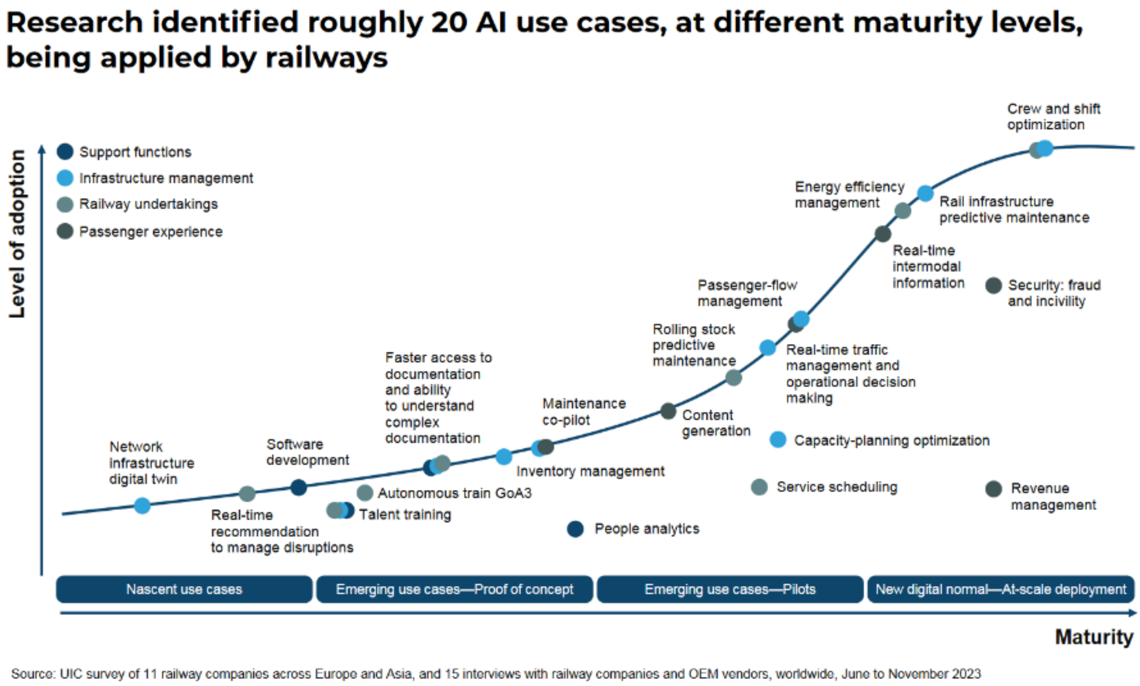

Figure 3: AI use cases in rail industry (Source: McKinsey and UIC 2024)

The report organizes use cases into four application domains: railway undertakings, infrastructure management, passenger experience, and support functions. This deliverable focuses on the first three domains, as they are more relevant to metro and railway operations. In contrast, AI applications in support functions tend to be generic and not specific to the unique needs of the rail sector.

Railway undertakings

About 40% of surveyed railway companies have adopted AI for **crew and shift optimization**, improving staffing schedules by balancing coverage needs with employee preferences. This has led to safer, more resilient operations across roles like drivers, onboard staff, and maintenance crews, with reported labor cost reductions and 10–15% shift optimization.

AI for energy efficiency in rail is gaining traction, aiming to reduce consumption through optimized routing, maintenance, and train operation. Tools like eco-driving systems provide real-time driving recommendations, with reported energy savings of 10–15%.

Predictive maintenance for rolling stock is used by about half of surveyed rail companies, focusing on critical assets prone to failure. Challenges include limited data access, though newer, connected trains are improving this. Reported benefits include a 15% boost in reliability, 20% lower maintenance costs, and 30% fewer breakdowns.

Around 30% of surveyed rail companies are testing optimization algorithms for s**ervice scheduling**, using AI to assess demand, prioritize paths, and manage constraints like station capacity and workforce. Deutsche Bahn, for example, combines AI and big data to predict train movements and provide real-time updates to passengers.

Around 20% of surveyed rail companies are testing semi-autonomous and driverless GoA3 (Grade of Automation) trains, aiming for a 30% increase in capacity, 30-45% reduction in energy use, and lower labour costs. In 2019, China launched the world's first fully autonomous high-speed railway, connecting Beijing to Zhangjiakou at 350 kph for the 2022 Winter Olympics.

Around 10% of railway companies are exploring AI-powered digital twins for **real-time recommendations to manage disruptions**. This technology aims to enhance decision-making, minimizing the impact on costs, passenger experience, and employee satisfaction during irregular operations.

Infrastructure management

AI-driven **crew and shift optimization** in railway undertakings has improved scheduling, ensuring better safety and resilience by generating optimal plans for crew allocation.

All major infrastructure managers interviewed use AI-driven **Rail Infrastructure Predictive Maintenance** to prioritize critical assets, relying on specialized trains to detect track issues. This approach typically reduces unplanned downtime by 15-25%, cuts maintenance costs by 15-30%, improves failure detection by over 100%, and reduces delays by 20%.

AI-based systems for **Passenger Flow Management** analyse passenger movement patterns, predict peak travel times, and dynamically adjust staffing or direct passengers to less crowded areas in real time. Using sensors, surveillance cameras, and machine learning algorithms, these systems optimize passenger flow, reduce bottlenecks, and enhance station security.

Around 25% of railway companies are using AI for **Capacity Planning Optimization**, aiming to maximize network capacity while addressing operator, maintenance, and external needs. This can lead to a 7% to 9% increase in network capacity.

Around 60% of infrastructure managers use AI for **Real-time Traffic Management** to optimize routes and reduce disruptions through automated, centralized control. This system allows for proactive planning, addressing path conflicts and predicting delays, ultimately improving network capacity, on-time performance, and passenger experience., flagging issues and providing dispatchers with alternative options.

20% of railway companies interviewed are investigating the application of advanced analytics and machine learning in **inventory management** to forecast demand and optimize supply levels, with the goal of improving accuracy, reducing lead times, minimizing excess inventory, and boosting working capital.

A few companies are exploring the use of generative AI to assist maintenance technicians through a **maintenance co-pilot**. This AI tool can analyse equipment manuals, quickly diagnose issues, and provide instructions for necessary procedures. It aims to improve efficiency, reduce costs, and address challenges in talent retention and attraction.

About 10% of railway companies are exploring AI-powered **network infrastructure digital twins** to optimize infrastructure design and construction. This use case aims to cut capital expenditure by 10–15% and reduce project overruns by 6 to 18 months.

Passenger experience

Around 5% of surveyed railway companies have adopted AI-based **revenue management systems**, moving beyond traditional rule-based approaches. These solutions require reservation-based systems and use machine learning to forecast demand and optimize pricing based on factors like route, time, and demand levels. In one case, this approach led to a 3–8% revenue increase and higher customer numbers by aligning prices with demand.

About 25% of railway companies use AI-powered vision and predictive algorithms to enhance **security (fraud and incivility protection).** Initially deployed for health compliance, such as mask-wearing, these tools now help optimize security team deployment across networks. The result: 10% lower security costs, reduced fraud, increased ridership, and improved customer experience.

Around 40% of surveyed railway companies are using AI to deliver **real-time intermodal information**, helping passengers plan seamless journeys across rail and other transport modes. This has led to a 10–15% increase in customer satisfaction and stronger customer engagement.

Passenger Flow Management is vital to enhancing the passenger experience, and many railways are leveraging AI to streamline boarding and disembarkation. Systems like the intelligent video analytics (DIVA) monitor crowd density in real time and guide passengers via platform displays to less congested areas. Additionally, predictive modelling helps rail operators take preventive measures to manage passenger flow during peak hours or busy travel seasons.

Content Generation for Passengers is being used by 40% of interviewed railway companies to enhance customer experience through AI-driven personalized communication and real-time updates. For example, an AI-based interactive voice response system that engages directly with customers, either as a digital avatar, voice over the phone, or a physical robot.

Table 3: AI Use Cases (Source: MCKINSEY AND UIC 2024)

AI APPLICATION	USE CASE	DESCRIPTION
Railway undertakings	Crew and Shift Optimization	AI algorithms optimize crew scheduling by balancing coverage with employee preferences, improving operational efficiency.

AI APPLICATION	USE CASE	DESCRIPTION
Railway undertakings	Energy Efficiency	AI tools optimize train routing, maintenance schedules, and driving techniques to reduce energy consumption and improve efficiency.
Railway undertakings	Predictive Maintenance for Rolling Stock	AI-based systems monitor train health, predict failures, and automate maintenance tasks to improve asset reliability and reduce downtime.
Railway undertakings	Service Scheduling Optimization	AI analyses demand patterns and constraints to optimize train schedules, ensuring smooth operations and efficient resource allocation.
Railway undertakings	Autonomous Trains	Semi-autonomous GoA3 trains use AI to automate operations, enhancing capacity and energy efficiency while reducing labor requirements.
Railway undertakings	Disruption Management	AI-powered digital twins simulate real-time scenarios to optimize decision-making during disruptions, improving operational resilience.
Infrastructure management	Predictive Maintenance	AI systems monitor infrastructure health, predict potential failures, and optimize maintenance scheduling to minimize downtime and cost.
Infrastructure management	Passenger Flow Management	AI-driven systems analyse crowd density and passenger movement, adjusting staffing and guiding passengers to optimize flow and reduce congestion.
Infrastructure management	Capacity Planning Optimization	AI tools assess network conditions, operator needs, and external factors to optimize resource allocation and increase overall network capacity.
Infrastructure management	Real-Time Traffic Management	AI algorithms manage traffic flow in real-time by optimizing routes, predicting delays, and adjusting to dynamic conditions, enhancing operational efficiency.
Infrastructure management	Inventory Management	Advanced AI systems forecast inventory demand, automate stock management, and optimize supply levels to reduce waste and improve efficiency.
Infrastructure management	Maintenance Co-Pilot	AI-driven maintenance assistants help technicians diagnose issues, access manuals, and suggest corrective actions, improving maintenance efficiency.

AI APPLICATION	USE CASE	DESCRIPTION
Infrastructure management	Digital Twin for Infrastructure	AI-powered digital twins simulate infrastructure design and performance to optimize construction, reduce costs, and streamline project timelines.
Passenger experience	Revenue Management	AI-based systems adjust pricing dynamically based on demand, optimizing revenue and improving customer segmentation and targeting.
Passenger experience	Security (Fraud and Incivility Prevention)	AI vision systems monitor behaviour and detect anomalies, deploying security resources efficiently to prevent fraud and improve passenger safety.
Passenger experience	Real-Time Intermodal Information	AI integrates data from various transport modes, providing real-time travel recommendations to passengers for a seamless journey.
Passenger experience	Content Generation for Passengers	AI systems generate personalized communication and updates for passengers, enhancing engagement and delivering timely, relevant information.

3.2 METRO OPERATIONS & AI: AN INDUSTRIAL STATUS QUO

AI is gaining increasing popularity in industry as it can make processes more efficient, faster, and cost-effective. Companies are therefore increasingly investing in the research and development of AI technologies (Capgemini, 2025). Thereby, the railway sector benefits from a steadily growing amount of available data that can be used for AI and machine learning solutions (Visser, 2025). Since 2017, GenAI has been gaining importance in the rail industry, with interest further increasing since 2022 through the release of applications such as ChatGPT (Melnikov et al., 2024). The growing relevance of this topic is illustrated, for example, by InnoTrans, which has reserved a dedicated area for AI solutions since 2024. It is therefore not surprising that manufacturers and operators are already using numerous AI applications and constantly looking for new ways to implement AI in rail and metro operations. The railway industry's AI transformation is supported by an expanding network of technology partners and solution providers. Strategic technology partnerships between railway manufacturers and tech companies have become increasingly important as evidenced by several high-profile collaborations. Notable examples of these collaborations include Siemens' partnership with Microsoft (established 2020) and Altair Engineering Inc. (established 2025), focusing on cloud computing and digital twin solutions In addition, AI companies like Nvidia are cooperating with industrials partners such as Siemens (established 2022) and Hitachi Rail (established 2024) to improve signalling systems through

AI, while Hitachi Rails partnership with Guavus (established 2017) specializes in real-time analytics for predictive maintenance.

Despite the enormous potential and numerous ideas for AI use cases within the sector, it is important to consider that the integration of AI into metro operations presents several challenges due to the black box problem. This is because many of the use cases interesting for metro operations, such as autonomous driving, AI-based signalling control and automatic safety systems for collision avoidance fall into the category of "safety-critical" solutions. In these cases, highly complex AI mechanisms are necessary to process the abundance of data. These are therefore "black-box solutions", where it is not directly traceable how the AI arrives at its solution/decision based on the deep learning models. While these black box solutions can be used without problems for non-critical solutions such as live updates and route calculation for customers, etc., it is more challenging for solutions involving decision-making in accidents, etc. The reason for this is that this traceability is precisely what is required when it comes to immediate decisions affecting passenger safety and legal liability. Hence, there is a trade-off between model complexity and interpretability, emphasizing the need to make AI more transparent and trustworthy to enable the use of AI in safety-critical applications. In addition to these technical challenges, organizations must navigate compliance with the EU AI Act, creating a distinct regulatory landscape for AI implementation in Europe. While AI solutions are being rapidly deployed across markets such as China, the US, and Japan, their adoption in the EU requires careful consideration. Despite proven success records in international markets, the EU's comprehensive data protection framework and AI governance standards require substantial modifications to existing solutions. This regulatory environment, while ensuring high standards of data protection and algorithmic accountability, inevitably extends implementation timelines and increases complexity for AI deployment in the European market.

In contrast to conventional railway systems, metro systems function as relatively self-contained operational environments. These systems, characterized by their high degree of automation, generate substantial amounts of operational data, creating an ideal ecosystem for AI solution implementation. Particularly noteworthy is the highest automation level GoA4, which enables completely driverless operations and represents the pinnacle of metro automation technology.

To get an overview of the currently available AI solutions in metro systems, a comprehensive web-based analysis was conducted examining the AI solutions deployed by the nine leading railway manufacturers and major railway operators. The study focused on identifying current solutions and evaluating their applicability or potential adaptation for metro operations. It is important to acknowledge that the research findings are partially based on corporate marketing materials, and detailed technical specifications were not accessible. Nevertheless, combining the available information with industry-specific assumptions reveals that die existing AI solutions in metro operations are predominantly focused on operational efficiency, predictive maintenance, automation, safety & risk mitigation, as well as customer experience. The identified AI functions identified in this area can be derived from the table below.

Table 4: AI Use Cases from Industry perspective (Source: Siemens 2025)

OPERATIONAL EFFICIENCY	PREDICTIVE MAINTENANCE	AUTOMATION	SAFETY & RISK MITIGATION	CUSTOMER EXPERIENCE
Prediction and optimization of energy consumption	Pattern recognition for track conditions	Automated train operations	Obstacle detection	Smart boarding management
Network capacity maximization	Real-time condition monitoring	Autonomous depot operations	Environmental Monitoring	Personalized travel recommendation and real-time information about delays and routes
Passenger flow optimization	Automated diagnostic systems	Self-learning traffic management	Computer Vision for platform monitoring	Crowd flow optimization
Real-time traffic management	Fault detection and analysis	Automated decision-making systems	Emergency response automation	Interactive passenger assistance
Dynamic timetable adjustments	Maintenance schedule optimization	Dynamic route adjustments	Crowd density analysis	Smart ticketing solutions
Automated traffic flow optimization	Wear and tear analysis	Smart signalling systems	Collision avoidance system	Dynamic pricing and fare calculation
Resource allocation optimization		Automated incident-response	Security threat detection	

Current evidence demonstrates that AI primarily serves as a supportive technology rather than a complete replacement for existing solutions in the railway sector. This approach is largely attributed to the previously discussed black box problem, which presents significant challenges for implementing pure AI-controlled systems. It is important to highlight that there is currently increased research in the field of explainable AI by both academic and industry partners. An example of this is the research conducted by Yushan Liu at Siemens. Yushan Liu employs techniques such as model interpretability and explainability algorithms to elucidate AI processes. These methods enable AI systems to provide insights into how they arrive at specific conclusions. These advancements aim to facilitate a better understanding of the reasoning behind AI-driven decisions. Depending on the progress of this research stream, it may become feasible in the future to utilize AI for safety-critical functions.

Despite these challenges, leading railway technology companies already successfully integrated various AI technologies into their existing solutions, focusing on three primary application areas: Train Control and Monitoring Systems (TCMS), Communications-Based Train Control (CBTC), and Predictive Maintenance. Within these domains, AI plays a crucial role in data integration, analysis, automation, and control processes. Particularly noteworthy is the growing implementation of AI-powered solutions for real-time analysis of image and video data, which generates valuable additional insights for operational optimization.

3.2.1 AI FOR TCMS SYSTEMS

TCMS serves as the train's sophisticated “nervous system”, orchestrating a comprehensive network of computer-based control and monitoring functions. At its core, this complex system seamlessly coordinates and oversees a wide range of essential operations throughout the vehicle. These include dynamic power regulation for drive control, safety-monitored door operations, and intelligent climate control that adapts to external temperatures while optimizing energy efficiency based on passenger volumes. Additionally, it manages passenger information systems and maintains continuous surveillance of all critical train components. Within this advanced framework, AI applications enhance the TCMS's capabilities by focusing on three fundamental areas: sophisticated data integration, instantaneous analysis of operational parameters, and adaptive system controls. This intelligent integration results in significantly improved train operation efficiency while maintaining unwavering adherence to the highest safety standards. The synergy between traditional control systems and AI-enhanced functionality creates a robust and responsive platform that optimizes both performance and reliability.

A typical example of AI image processing for TCMS systems are Platform Screen Door Monitoring Systems for GoA4 operations. These systems combine various sensor technologies such as high-resolution cameras, LiDAR, and infrared sensors with advanced AI-supported image processing to ensure comprehensive monitoring of the platform area. Through the implementation of edge computing and redundant processing units, real-time decisions are enabled with the highest reliability. This means, that the system automatically detects people in danger zones, continuously monitors the critical gap between train and platform edge and ensures precise door alignment. This information is then transferred to the TCM System. In case of potential hazards, an immediate response can be triggered, such as automatic emergency braking or door blocking.

3.2.2 AI FOR CBTC SYSTEMS

CBTC represents an advanced railway signalling and control system that enables automated train operation through continuous wireless communication between trains and wayside equipment. The system optimizes rail traffic through comprehensive management of train movements across the entire network, with automatic route setting, schedule regulation, and conflict resolution serving as central functions. Optimal operational efficiency is achieved through real-time adaptation to changing traffic conditions, management of train headways, and coordination of platform arrivals and departures.

The AI applications in CBTC systems primarily focus on optimization and support functions. In the area of traffic optimization, AI algorithms analyse historical and real-time data to optimize schedules, train headways, and energy consumption. Simultaneously, predictive maintenance through AI-powered analytics enables early detection of potential issues in system components and infrastructure.

Passenger flow management utilizes AI to process data from various sources such as ticket gates, platform sensors, and train load sensors to predict passenger volumes and optimize service patterns. In the area of decision support, AI assists operators in the control centre with managing complex operational scenarios and responding to disruptions. However, it is important to emphasize that safety-critical functions continue to rely on deterministic, Safety Integrity Level 4 (SIL4)-certified systems rather than AI.

3.2.3 AI FOR PREDICTIVE MAINTENANCE

Artificial Intelligence is increasingly becoming an integral part of modern asset management systems, particularly in the area of predictive maintenance. Examples of such solutions include the Alstom HealthHub platform, Hitachi's HMAX solutions platform, Stadler's Diagnostic System SDS, Siemens Railigent X Health States, and CAF's LeadMind solution.

Most of these solutions are based on cloud-systems that collect and analyse data from various sources to create precise maintenance forecasts. Designed as advanced diagnostic tools, these platforms operate independently of safety-critical systems, allowing for the safe use of AI technologies. Consequently, these systems represent a significant advancement in maintenance technology, enabling the transition from reactive to proactive maintenance. By integrating intelligent diagnostic functions, companies can optimize their maintenance processes, reduce manual inspections and downtime, and improve overall system reliability

It is important to note that different providers and metro operations must meet varying requirements, resulting in diverse functionalities within these platforms. This diversity ensures that the specific needs of different industries and applications are adequately addressed, providing tailored solutions that enhance the effectiveness and efficiency of maintenance operations. Consequently, solutions like Siemens Railigent X Health States and Alstom HealthHub are not identical and cannot be used interchangeably. Each platform offers unique features and capabilities designed to meet specific requirements. However, in most cases, the implementation scope encompasses the following two main areas:

- **Predictive Maintenance of Vehicles:** AI solutions continuously monitor critical components such as traction systems, doors, brakes, and HVAC units, enabling precise maintenance scheduling and reducing unnecessary downtime. This proactive approach has demonstrated significant improvements in fleet availability and reliability.
- **Predictive Maintenance of Infrastructure:** AI solutions provide comprehensive monitoring of track systems, power distribution, signalling equipment, and station facilities. The technology analyses vast amounts of sensor data in real-time, identifying potential issues before they impact service operations. This capability has proven particularly valuable in maintaining complex metro networks where traditional inspection methods are time-consuming and often insufficient.

To highlight the use of AI in the field of predictive maintenance, the following chapter will describe the Siemens Railigent X Health States and VEMS solutions in more detail. The aim of this description is to better understand the underlying AI technologies and functionalities of predictive maintenance solutions.

Railigent X Health States is an application from the Railigent X Cloud that leverages AI and IoT technologies to transform maintenance processes. It continuously collects and analyses diverse data streams from multiple sources. Through real-time condition monitoring, failure prediction algorithms, and performance analytics, proactive maintenance strategies are enabled. The integration of digital twins and continuous asset health monitoring provides a detailed understanding of equipment status and performance trends. While these data provide different perspectives on the condition of the different components, it’s essential to interpret them in the right manner and draw the right conclusions. Railigent X Health States achieves this by leveraging advanced analytics and machine learning algorithms, to transform the data into actionable insights using an AI-based decision-support model for consistent assessment and maintenance recommendations Figure 4. Through this approach Railigent X Health States helps to draw the right conclusion of the gathered data. This proactive approach not only enhances asset availability but also reduces maintenance costs and extends component lifecycles. The system's ability to integrate with existing infrastructure while providing forward-looking maintenance insights makes it indispensable for modern rail operations.

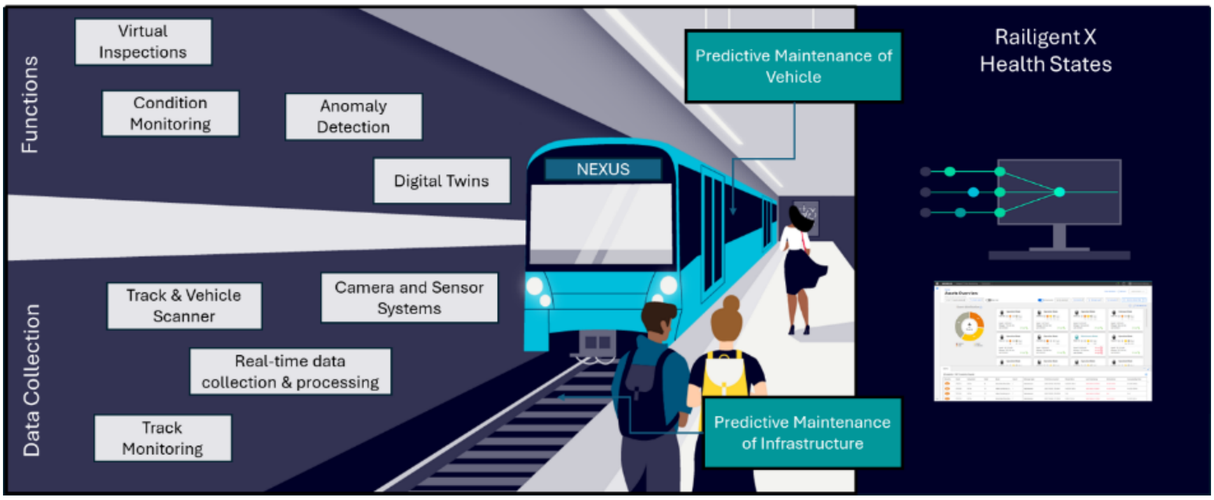

Figure 4: From Data Collection to predictive maintenance (Source: Siemens 2025)

Similar to TCMS and CBTC solutions, predictive maintenance systems have significantly advanced through the integration of AI-powered visual inspection technologies. Building on these advancements, industry leaders have developed innovative solutions such as Siemens' Vehicle Equipment Maintenance System (VEMS) and Alstom's TrainScanner. These systems employ cutting-edge laser and camera technology to monitor and assess train and metro components by capturing high-resolution images and precise measurements as trains pass through specialized measurement facilities. Advanced AI algorithms and image and video analysis systems automatically detect anomalies, including component wear, structural damage, and dimensional deviations, facilitating early intervention and optimized maintenance scheduling.

VEMS provides a suite of automated inspection equipment for rail vehicles, utilizing AI for image and video analysis, as well as sensor and laser technologies to evaluate their service availability and safety. This equipment gathers data on various train components, which is subsequently transmitted to the Railigent X Health States Application. Figure 5 presents an overview of the different solutions and systems that collect various types of vehicle data. The data collected is streamed directly into asset management systems like Railigent x Health States, enabling real-time analysis and continuous monitoring. To give readers a better understanding of the different solutions and their underlying functions and purposes, the systems are presented in more detail below:

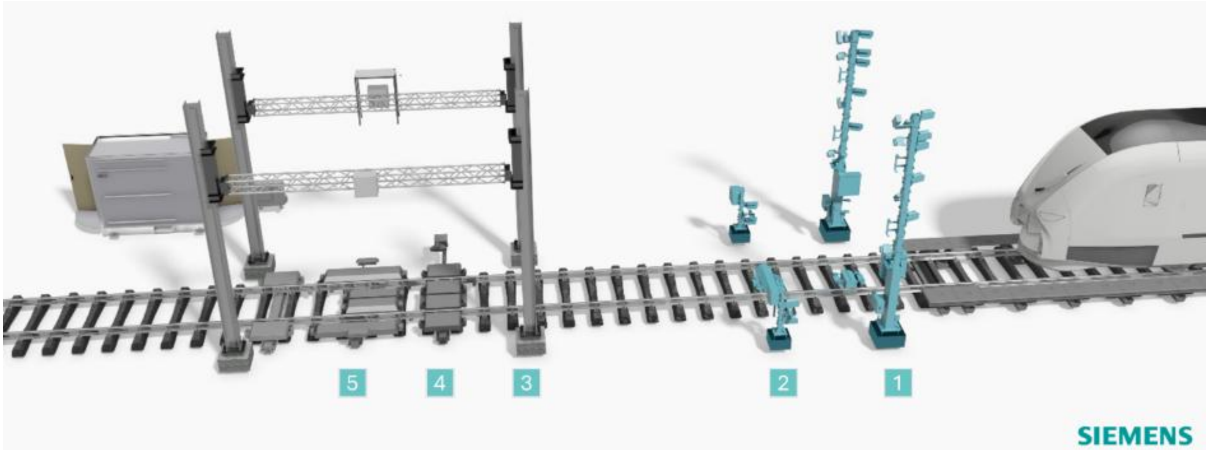

Figure 5: Siemens VEMS Solutions for Data Collection (Source: Siemens 2025)

System 1: VEMS for wheel tread measurement - The Wheel Tread Measurement System uses patented technology to generate a complete 360° model of the wheel tread as it rolls by. The system uses this data to analyse each wheel for cavities, flats, and out-of-roundness in milliseconds instead of the hours that a current full-vehicle inspection can take. This approach also eliminates the time-consuming process of stopping a train and lifting each axle to make a manual 360° measurement.

System 2: VEMS for visual inspection - The Visual Inspection System replaces traditional labour-based inspections with computer vision and machine learning. The modular design allows the system to be configured to meet the maintainer's business case. Options range from a system that monitors an individual bolt to a full 360° whole-vehicle integrity solution. The system generates tabular reports for specific measured values and a complete image file for audit and review purposes.

System 3: VEMS for pantograph wear measurement - The fully automated VEMS for pantographs measure the integrity of the components. The recorded data can be trended to derive wear rates and predict service life. And the measurement records can be stored, analysed, viewed, and reported in the MRX data management system.

System 4: VEMS for brake measurement - VEMS for brakes are based on high-precision, non-contact measurements of the friction materials and brake components. These systems measure the wear of brake pads, brake discs, brake blocks, and brake shoes and can compare wear trends across axles, bogies, trains, and fleets. Any missing components, such as like brake pads, are reliably identified.

System 5: The Wheel Profile Measurement System provides highly accurate automated measurements of all wheel parameters required by international standards as well as additional parameters and reports focused on reducing costs through increasing wheel life. The hardware design is focused on replaceable units that ensure industry-leading availability of the system with low lifetime costs.

3.2.4 SUMMARY

The implementation of AI in metro operations demonstrates a strategic and measured approach to technological integration. The current AI landscape is characterized by selective implementation in mostly non-safety-critical applications, with a strong focus on operational optimization, efficiency improvements, predictive maintenance solutions, and enhanced customer service applications, all while maintaining strict adherence to safety standards and regulations. Hence, rather than pursuing complete system transformation, the industry has adopted AI selectively and pragmatically, focusing on enhancing existing systems while ensuring operational safety and reliability.

To extend AI applications to safety-critical functions, solutions for developing more transparent AI systems are necessary to address the current "black box" challenge. Within academic research and industry, various solutions for the explainability of AI are being explored. It is important to note that different solutions are used depending on the data, which means that a one-size-fits-all solution for AI cannot be developed. However, resolving the challenge of the black-box systems could significantly expand AI applications across metro operations while maintaining essential safety standards.

The increasing use of AI for image and video analysis has opened new possibilities for information processing and input generation resulting in different solutions and use cases for metro operations.

To consider is that regional differences in AI adoption remain notable, with rapid implementation in China, the US, and Japan, contrasting with a more measured approach in European markets due to stringent regulations. This creates an ongoing need to carefully balance innovation with regulatory compliance, particularly in markets with comprehensive data protection frameworks and AI governance standards. This balanced approach to AI integration reflects the industry's commitment to leveraging new technologies while ensuring safe and reliable metro operations. Hence, the focus remains on enhancement rather than replacement, indicating a mature and pragmatic implementation strategy that prioritizes operational stability alongside technological advancement.

3.3 METRO OPERATIONS AND AI: INSIGHTS FROM EXPERTS WORKSHOPS

3.3.1 WORKSHOP 26 MARCH 2025 IN VIENNA

3.3.1.1 GENERAL DISCUSSIONS ON ADAPTABILITY ANALYSIS

When discussing about challenges regarding planning and optimizing the service, it was remarked the importance of planning for the long term also considering some parameters, for example dwell time in the demand forecasting (to know how to estimate the right dwell time is a challenge for some operators).

About planning for the short term, the challenge is reliability. At long-term, demand forecasting, although models are available and widely used, some assumptions still need to be made. Of course, these assumptions have an impact on the financial side (e.g., buy new trains, extend/update the infrastructure). Another challenge for EAB members is to regulate the entrance flow in the stations when reaching the maximum capacity. Demand evolved after COVID, with a distribution over the week very different compared to pre 2020 (increased working from home, more demand at the weekends). In the planning of the service, another challenge is the presence of different stakeholders in the landscape (for example political bodies or different authorities for different transport mode, that are sometimes not communicating properly, although some synergies are starting to be exploited nowadays). Another aspect to be considered is ticketing that is sometimes very rigid and does not reflect a demand that is flexible. Maintenance has an influence on service planning.

Importance of resilience, for example towards climate change events, was remarked too.

About demand, and specifically about counting methods, operators use different tools: turnstiles, sensors, historical data, statistics, estimations (that have to be as much accurate as possible). Historical data is still widely used for planning. To create accurate origin-destination matrix would surely allow better organization of the service. There are experiments with GPS or Bluetooth used for tracking people, although not much diffused.

Additional gaps and limitations for planning the service have been remarked: data accuracy is very critical (prove that data is reliable); data integration ("speaking the same language"); exploitation of scenarios that are harder to model (e.g., non-peak hour; planning maintenance for minimizing disruptions).

Importance of an integrated approach taking into account metros but in conjunction with other modes, is paramount, and also the relevance to link urban and transport planning (as shown by Wiener Linien in the morning). Concluding this session, it was remarked that contingency plans must be accurate.

3.3.1.2 WORK SESSION – AI AND DATA SCIENCE IMPLEMENTATION IN METRO OPERATIONS

Participants were asked to answer the following pre-prepared questions, thus animating a debate that will feed NEXUS project activities and WP6 deliverables.

- What are the most relevant use cases for ML / AI that metro operators see?
- Has data already been collected to support such a use case?
- What are human tasks that can be supported by or even automated with ML / AI?
- What are the most relevant datasets for metro operations that are already available and can be shared with researchers in Nexus?

Different use cases about AI/IoT/Machine Learning applications to metros have been mentioned during a brainstorming session. Among the most relevant: predictive maintenance (status of asset); knowledge management (chatbot internally used by the operator with their staff, for example to know security procedures or procedures in general); planning of services (adapting service to demand); OCC operator support (prioritization of tasks/warnings); track inspection; customer service (overcoming language barriers with customers, especially in touristic destinations); and prediction of demand; aggression monitoring, alerting the operator (note: there is research on this, operators might be interested); dynamic adaptation of the train speed or stations in which the train stops if nobody on platform; detecting pollution/trash (giving "live" instructions for improving cleanness of vehicles/stations. If limited to a study, it was considered interesting to explore the correlation between weather and use of metro. Other "out of the box" applications in the future: pickpockets tracked with face recognition; lost and found; suspicious behaviour detection (all the above need to be a regulatory framework that would enable them); cyberthreats identifications. When it comes to AI, it was remarked that although technologies are there (and/or in advanced development phase), the training of the staff remains a key pre-requisite for their effective exploitation.

Q1 What are the most relevant use Cases for ML / AI that metro operators see?

- Predictive maintenance, lifespan of the asset, increase efficiency, cost savings asset dependent. Improvements in cost and add cost savings to maintenance.
- Support operator with real time data, visualizations of alarms,
- AI for knowledge management, internal chatbots asking questions about procedures. What are the security/safety procedures for a type of task (safety when working with live power?) challenges with accuracy of retrieved information/generated answers. Balancing between accuracy and interpretation allowance. Driver might need to find a procedure quickly.
- Create predictive model of passenger travel routes, build statistic about a station, increase of passenger in station because of event in the town,
- Build origin/destination matrix with AI
- Olympics, give information to people in their language, and translate new information simultaneously to customers
- Giving operators different warnings based on activities?
- Detect, people/objects in the system that are not normal
- Interest in aggression monitoring? Station and train would be useful, highlighting things

Q2 Has data already been collected to support such a use case?

- Soiling, pollution of vehicle? Right now, manual checks at the end of the line.
- Timetables of stop times, durations? Historical data, main usecase to prevent services overloading during concerts etc. weather? There is relation with weather, more people take metro during bad weather, but they don't know how to use it. Interest: for a study. Universities already do first studies on weather and passenger demand, external factors and how the affect the demand of the metro, how to predict ahead of time. You need to predict ridership instead of guessing for planning. What can metro do to adapt to the external factors, because flexibility is limited.
- Reduce top speeds or delay trains during low demand. Interesting? Sometimes mandatory intervals and KPIs, but saving power is interesting.
- Safety application? No imaged safety tasks, the best solution in a situation shouldn't be chosen by a robot but by the experience of an operator. – pickpocketing detection, lost and found also a huge topic

Q3 What are human tasks that can be supported by or even automated with ML / AI?

- Platform safety, strange or dangerous behaviours, Washington have experts that can detect mental health issues via cctv and alert security. Understand risky behaviour in advance, and alert. [Passenger] Behaviour detection is mainstream in US but not applicable in EU. Ai application regarding hidden objects have been started, but difficult to implement in real cases, AI act and GDPR are making it difficult. Policing is extremely strict.
- Anomalies in cybersecurity is widespread. Common trends is ransomware, innocent email infects system, USB attached to machine, etc.

The work session concluded with a reminder to all participants about the importance of their feedback—through surveys, interviews, or direct contact..

3.3.2 PARTNER WORKSHOP 22 APRIL 2025 IN GRAZ

3.3.2.1 WORKSHOP GOALS

- Identify industry relevant use cases on ai in future metro operations
- Create Big Picture: IoT, Big Data, and AI applications in future metro operations
- Collect and visualize AI use cases from the perspective of the OEM (Siemens)
- Briefly describe and categorise UCs in
    - Siemens solution or available as a product
    - Solution relevant for Siemens, but not in use
    - Solution not relevant for the time being, but technically feasible
- Evaluate content for upcoming deliverable D6.3
- Consensus Siemens - ViF on the next steps in the project

3.3.2.2 WORKSHOP CONTENT

On 22 April, the partners Siemens and Virtual Vehicle met for a bilateral Nexus workshop in Graz. The aim was to familiarize themselves with the perspective of industry (OEM) in particular and to gain an overview of which AI-supported solutions are relevant in the industrial environment.

A detailed distinction was made as to which approaches are still under development and which approaches are already available as products. Furthermore, products already in use at a metro operator were recorded. A total of 43 possible use cases were identified, discussed and recorded with regard to manufacturer, potential, classification, goal, function, assumed use of AI, and source (link). All use cases were checked for potential applications in metro operations and finally documented in master table.

The master table with a complete overview is attached in Annex.

3.3.2.3 WORKSHOP RESULTS AND NEXT STEPS

- Stick to the Soiling UC “operational readiness detection”.
- Obstacle Detection will be only theoretically described but no further analysis.
- Simulation of Metro operation after checking the feasibility (energy optimization, transport capacity optimization, potential of GoA4, etc.).
- Cost and trade-off CCTV processing, customer-oriented priority list / budget.
- Investigation of audio files (spraying, vehicle monitoring, etc.).
- Create a questionnaire and deliver it via UITP to rate the Use Cases by the Metro Operators

4 DEEP DIVE: AI IN SPECIFIC USE CASES FOR FUTURE METRO OPERATIONS

4.1 PREDICTION OF CROWDING BASED ON EXOGENOUS DATA SOURCES

In recent decades, the increasing urbanization and expansion of public transport networks made the development of accurate prediction models increasingly crucial to forecast crowding and passenger flows. A reliable prediction of the public transport demand not only allows optimization of the management of the infrastructure, but also allows improvement of the user experience, reduces passenger waiting time, and mitigates the risks connected to crowded spaces.

Passenger flow prediction methods greatly improved in the last decades thanks to technological progress and data availability. In the '70s and '80s predictions were based on classical statistical models, such as linear regressions and moving average: methods that failed to capture complex patterns in the data.

The introduction of automatic data gathering systems, like smart card readers and electronic ticket barriers, changed the way of predicting crowdedness. The greater amount of available data enabled more sophisticated algorithms, capable of modelling seasonality and other form of cyclic fluctuations which are typical of public transport. While these models can capture basic trends and patterns, they fail in scenarios such as special events or sudden changes in weather. Moreover, this kind of model cannot automatically adapt in changes in the patterns and require a significant amount of human supervision.

The 2000s saw the emergence of machine learning as a prediction tool. The usage of techniques like Support Vector Machines and Random Forests allowed to model non-linear relationships in the data and to incorporate context variables like special events, weather conditions, and patterns in the user behaviours.

During the last decade deep learning techniques revolutionized this field once again: Recurrent Neural Networks (RRN) and Long Short-Term Memory (LSTM) Networks are particularly effective in capturing complex time-dependent patterns, while Convolutional Neural Networks (CNN) are excellent for spatial analysis.

The COVID-19 pandemic introduced new challenges in predicting passenger flow: previously developed models struggled to make accurate predictions in this context. For this reason, new models capable of rapidly adapting their predictions to new conditions have been developed.

In this section the existing literature on this subject will be investigated, focusing on the different methodologies that have been adopted to predict passenger flows and, on those solutions, based on technologies such as machine learning and data analysis. Both traditional predictive models based on time series and regression, and newer approaches based on neural networks and deep learning will be analysed.

4.1.1 CLASSICAL METHODS

Classical methods to predict passenger flow are based on statistical methods that exploit the temporal structure of the data to generate predictions. The most common methods employed to perform this statistical time series-analysis are the three methods from the Autoregressive Integrated Moving Average (ARIMA) group.

ARIMA (Box & Jenkins, 1970) is one of the most used methods used to predict univariate time-series. This model is particularly useful when the data contains a trend, but not seasonality. It is not ideal for the crowding prediction use case as usually passengers follow seasonal patterns (e.g., differences in passenger behaviour during holidays and weekdays). The ARIMA model has been employed to predict passenger flow in (Feng & Cai, 2016; Tang, Zhao, Cabrera, Ma, & Tsui, 2019; Yan, Zhou, Zhao, & Wu, 2018).

Seasonal ARIMA (SARIMA) (Box & Jenkins, 1970) tackles this problem by adding the seasonality to the analysis. This model has been employed to predict metro passenger flow in (Milenković, Švadlenka, Melichar, Bojović, & Avramović, 2016).

Another evolution of the ARIMA model is Space-Time ARIMA (STARIMA) (Cliff & Ord, 1975). It extends the ARIMA model by introducing space-time dependencies between observations from distinct locations. It has been employed in (Duan, Mao, Zhang, & Wang, 2016) to predict traffic flow.

4.1.2 NEURAL NETWORKS

Differently from classical statistical methods, Neural Networks can learn complex patterns in passenger flow and exploit large datasets containing heterogeneous data such as historical data, weather data, extraordinary events, and information on the transportation network. Specialized architectures like RNN, LSTM Networks, and GCN are particularly effective in capturing the complex space-time dependencies in crowd prediction.

In (He, Li, Zhu, & Tsui, 2022) Convolutional-Recurrent Neural Networks have been adopted to capture the complexity of multiple graphs used to encode the spatial correlation between stations combined with exogenous data sources. The authors underline the importance of features like the network structure and the recent flow patterns. The developed model can predict passengers' flow both in and out of the stations and has been successfully employed in the context of the Shenzhen metro.

In (Yang, et al., 2021) the short-term prediction of passengers' flow has been made using the Wave-LSTM model, which combines the LSTM neural networks with the wavelet transform. The study has been conducted on the data coming from a single metro station of Beijing. The accuracy of this hybrid approach highlights the potential of combining time series analysis with neural networks.

Also (Ye, Zhao, Ye, & Xu, 2020) employ LSTM neural networks to capture the complex space-time correlations in the passenger flow. The proposed framework exploits distance in time and daily and weekly patterns of each station, combined with spatial information, such as near stations patterns. This framework has been successfully tested on Shenzhen metro data, demonstrating its ability to accurately predict crowding.

In (Wan, Cheng, & Yang, 2024) machine learning is integrated with time-series analysis. The approach proposed in this work consists in three phases: (1) decomposition of the data in trends, periodic components, and irregular fluctuation, (2) a more fine-grained decomposition using the Ensemble Empirical Mode Decomposition (EEMD) algorithm, and (3) normalize the obtained data and train the ML model.

In (Xiong, Zheng, Song, Zhong, & Huang, 2019) deep neural networks combined with LSTM and CNN methods have been used to predict passenger flows. This work demonstrates the capabilities of LSTM neural networks in making long term predictions. According to the results, this method is highly accurate in predicting rush hour passenger peaks and other anomalies during events. This approach has been tested using the Beijing metro data, an improvement over the traditional method.

In (Xie, et al., 2021) is presented a predictive model for sudden peaks in passenger flow. It considers both incoming and outgoing passengers and employs Wavelet Neural Network (WNN) to detect anomalies in the passenger flow, once the anomaly has been detected, it uses a Genetic Algorithm (GA) to enhance prediction accuracy.

In (Xue, Liu, Ren, Ma, & Gong, 2022) a model named Multivariate Disturbance-Based Hybrid Deep Neural Network (MDN-HDNN) is presented. It exploits smart card transactions and social media posts to enhance the crowding prediction. The correlation analysis described in this paper shows that the volume of social media posts can be used to improve the accuracy of passenger flow peaks predictions when compared to traditional methods.

In (Zhang, Han, Peng, Li, & Chen, 2022) the Graph Convolutional and Comprehensive Neural network (GCTN) model is described. This model combines several deep network techniques such as Transformers and LSTM to capture global and local time dependencies, while a convolutional neural network on graphs has been used to capture spatial correlations between stations.

In (Zhang, Chen, Cui, Guo, & Zhu, 2021) the ResLSTM model is presented. This model combines three advanced ML technologies: Residual Network (ResNet), GCN, and LSTM. ResNet is used to capture spatial correlations between metro stations, GCN extract topology information from the metro network, and LSTM model temporal dependencies. It exploits four types of data: incoming passenger flow, outgoing passenger flow, network topology and weather conditions.

In (Danfeng & Jing, 2019) a model based on multi-type attention networks is presented. This exploits several attention mechanisms to extract features from multiple sources like past passenger flow data, exogenous data, and station information. Moreover, a hierarchical attention mechanism is implemented to model the relations between stations and lines, while embedding techniques allow combining different data types.

4.1.3 OTHER METHODS

In addition to classical models and neural networks, various alternative approaches have been developed to improve passenger flow forecasting in metropolitan networks.

In (Toto, et al., 2016) the authors present PULSE, a framework that allows the predictions of incoming passengers in metro stations. This model exploits two kinds of features: streaming features (i.e., temporal variable such as time of the day, weather conditions, past traffic), and station specific features (i.e., characteristics of the stations such as peak hour crowdedness, distance from the city centre, and average passengers' flow). PULSE can automatically choose the best model to apply to each specific station and optimize the set of features based on the local context of the station. It employs both classical methods (e.g., ARIMA) and machine learning methods (e.g., Random Forests).

In (Park, Choi, Kim, & Yoo, 2022) an approach based on clustering with the funFEM method has been proposed. This approach consists in two phases: (1) clustering of the metro stations based on the passengers' flow patterns and (2) forecast of the time series for each cluster. The study is based on the smart card transactions in the Seoul metro system as the main data source.

(Cheng, et al., 2024) is focussed on short term prediction of passenger flows. The authors employ a wide range of data sources and their method is based on the following pipeline: (1) initial selection of feature using Gray Relation Analysis (GRA) and SHapley Additive exPlanations (SHAP), (2) Empirical Model Decomposition (EMD) to obtain more interpretable components, (3) feature selection based on Spearman correlation coefficient, and (4) prediction using recurrence plot and picture information entropy.

In (Sun, Leng, & Guan, 2015) a method that combines Support Vector Machines (SVM) and wavelet transform is presented. The authors propose the following pipeline: (1) decomposition of the passenger flow time-series in low and high frequency components using wavelets, (2) predict the single components using SVM, and (3) reconstruction of the predicted series, again with wavelets.

4.2 DEMAND FORECASTING IN METRO OPERATIONS

4.2.1 CLASSIFICATION OF METHODS USED IN URBAN RAIL DEMAND FORECASTING

Demand forecasting, often conflated with Passenger flow prediction, plays a critical role in the strategic and operational functions of railway systems (Milenković & Bojović, 2016) serves as a foundational element for the planning and control of various domains, including transport operations, infrastructure development, and service provision. As Nguyen et.al. (2020) highlight, the forecasting of passenger flow demand is particularly effective in optimizing metro service schedules, improving passenger flow management, and supporting effective policy-making and planning. Accurate demand forecasting enables railway operators to align transport supply with anticipated demand, thereby enhancing overall system efficiency.

Milenkovic, et.al, (2013) also emphasised that a thorough understanding of existing passenger travel patterns is essential to identify and analyse existing traffic related challenges. The influx of passengers during peak hour surges whether predictable such as during morning or evening commutes or unexpected influx of passengers places a strain on the system. These fluctuations often lead to congestion, service delays and operational inefficiencies. As a result, metro operators frequently encounter difficulties to appropriately provide services needed to passengers that balances efficiency, cost-effectiveness and passenger satisfaction.

Despite its importance, demand forecasting is inherently limited by its inability to account for all future uncertainties. Unforeseen factors can significantly impact the accuracy and reliability of forecasts (Milenković & Bojović, 2016) .

Demand forecasting horizons are classified into three types as shown in Table 5. Long term forecast which look ahead to 5 to 10 years. Medium term forecasts which extend from 2 to 5 years into the future and Short-term forecast which predicts intervals between 6 to 18 months (Feng, et al, 2021). Outputs from short-term forecasting in particular plays a crucial role in immediate operational planning such as minute-based highway forecasting or hour based, or daily based forecasting for seat allocation in railways (Tsai & Wei, 2009). It is no surprise therefore that, Celebi, et.al, (2009) highlight short term forecasting as the key to the success of transportation planning and management like timetabling and resource allocation.

Table 5: Classification of Demand Forecasting (Source: Feng et. al 2019)

Time Horizons	Time frame	Focus
Long- Term forecast	5 -10 years	Strategic investments
Medium -term forecast	2 to 5 years	Planning
Short -term forecast	6-18 months	Operations

This literature explores a wide range of techniques used in demand forecasting specifically in metro and urban rail operations, highlighting the methods used for demand forecasting in metro operations to provide comprehensive understanding of the advancement in forecasting passenger demands as well as the future trends. Over the past decades, an extensive body of research has been contributed to enrich the forecasting approaches of urban rail transit. Both, qualitative approaches, such as Delphi, economic survey and analogical methods are as well as quantitative have been ways in which demand has been forecasted over time (Bai, 2016). Nonetheless, more interest has increasingly gravitated towards quantitative method of urban rail demand forecasting (Fang et.al, 2019).

Commonly used methods for rail transit demand forecasting include the traditional models, statistical models, machine learning and simulation software. Recent research has brought more attention to machine learning techniques which is a subset of artificial intelligence to accurately forecast passenger demand in transportation as a whole.

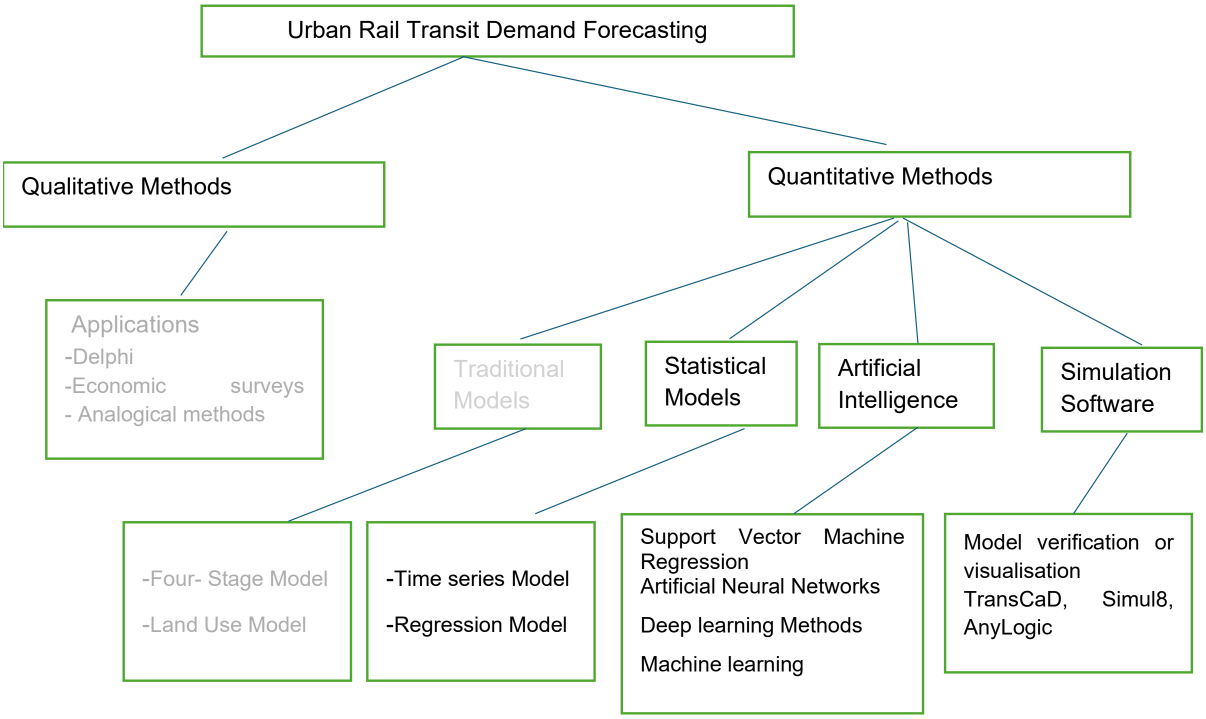

Figure 6: Classification of methods used in Urban rail demand forecasting (Source: Fang et.al 2019)

Figure 6 illustrates various quantitative methods of demand forecasting pointing out the growing use of artificial intelligence as a key future trend. Since there is limited research applying qualitative methods or traditional approaches in recent developments, this report focuses on quantitative techniques specifically those involving statistical models and artificial intelligence on passenger demand forecasting.

4.2.2 STATISTICAL METHOD OF DEMAND FORECASTING

Numerous studies have employed traditional statistical ways in which demand of passengers are predicted in railway systems, including linear regression, time series analysis, trending models, exponential smoothing, moving average and the AutoRegressive Integrated Moving Average, ARIMA (Halyal, et.al, 2022). In general, Demand Forecasting methodologies can be both qualitative and quantitative. Qualitative forecasting relies on insights provided directly by railway operators, while quantitative methods leverage historical data to identify trends and patterns. Table 6 shows a summary of studies on the use of statistical methods for passenger demand forecasting in urban rail transit.

Mendhe et al. (2025) presented a comprehensive study utilising ARIMA models to predict passenger traffic in metro systems using ticket reservation data from Pune Metro system, India. These ARIMA models identified seasonal trends and seasonal variations in ridership, enabling accurate predictions of passenger flow patterns.

Anvari et al. (2016) developed a time series forecasting framework based on Box-Jenkins methods for public transportation systems and the model was tested on real passenger traffic data from Istanbul Metro, the tests showed that the proposed framework is very effective and gives a higher accuracy. Based on Box-Jenkins, ARIMA model is found to be best suited for forecasting long term passenger demand and one of the most widely used time series models (Zhang 2003).

Kato et. al. (2017) developed a well-calibrated, accurate model to forecast urban rail travel demand in Tokyo's metropolitan rail network using mathematical modelling to help Tokyo's 15-year rail investment strategy.

In a comprehensive study, Tang et al. (2019) used various forecasting models, including time series model, ARIMA, linear regression and support vector regression to forecast short-term passenger flow at subway stations by utilising the data collected through an automatic fare collection system to evaluate the effect of temporal and spatial features as well as external weather influences on passenger flow forecasting.

To improve the granularity of temporal forecasts, Chuwang and Chen (2022) examined the comparative performance of ARIMA, Seasonal ARIMA (SARIMA), and the Facebook Prophet algorithm in predicting daily and weekly passenger demand. Their results suggested that Prophet outperformed SARIMA in daily forecasts, while ARIMA remained superior for weekly projections.

Milenkovic, et al, (2013) likewise applied the ARIMA in a state space form to forecast railway passenger traffic and model the rail passenger demand on Serbian railways addressing trends, seasonal and cycle variations providing a solid framework for modelling rail passenger traffic.

Alblooshi et al. (2024) investigated using three forecasting models SARIMA, Holt-Winters and Long Short-Term Memory (LSTM) to predict ridership demand for the Dubai Metro. SARIMA emerged the most accurate of the three models and effectively captured long trends and seasonal variations.

Guleria (2024) addressed the inaccuracies of forecasts in India particularly for the Delhi Metro due to unreliable travel demand models. It explores the application of probabilistic regression models especially the Gaussian, Negative Binomial, and log linear models to improve demand prediction.

Table 6: Summary of Studies of Traditional Ways for Demand Forecasting in Metro Operations (Source: AU 2025)

Study	Statistical Method Used	Statistical tool	Main Innovation	Time Horizon
Mendhe et al. (2025)	Time Series Forecasting	ARIMA	Used ticket reservation data to forecast metro demand with seasonal accuracy	Short to Medium Term
Anvari et al. (2016)	Time Series Forecasting	ARIMA – Box Jenkins	High-accuracy long-term demand forecasting using real metro data	Long term
Kato et al. (2017)	Mathematical Modelling	Custom demand model	Supported Tokyo's 15-year rail strategy with a	Long term

Study	Statistical Method Used	Statistical tool	Main Innovation	Time Horizon
			calibrated demand model	
Chuwang & Chen (2022)	Time Series Forecasting	ARIMA, SARIMA, Facebook Prophet	Compared models to identify best performers for daily and weekly demand	Short to Medium
Milenković et al. (2013)	Time Series Forecasting	ARIMA (State-Space)	Modelled rail demand accounting for seasonal and cyclical patterns	Long
Alblooshi et al. (2024)	Time Series Forecasting	SARIMA, Holt-Winters, LSTM	Identified SARIMA as best for long-term metro demand in Dubai	Long
Guleria (2024)	Probabilistic Regression	Gaussian, Negative Binomial, Log-Linear	Improved demand accuracy in India by correcting model bias from unreliable data	Medium

Collectively, these studies affirm that statistical forecasting methods are popular and most effective when historical demand data is available, and particularly useful for medium- to long-term planning where recurring temporal patterns can be exploited. However, they also underscore a significant limitation: the inability to forecast demand at new or future stations lacking historical data. This constraint is especially problematic during metro system expansions or when planning for newly urbanised areas, scenarios in which statistical methods become insufficient. It is precisely in such contexts that AI and data-driven modelling techniques offer a compelling alternative.

4.2.3 ARTIFICIAL INTELLIGENCE (AI) IN DEMAND FORECASTING

AI has emerged as a powerful complement to statistical methods in passenger demand forecasting, particularly in areas where conventional approaches lack flexibility or the capacity to handle complex, nonlinear, or data-sparse environments. Table 7 shows the summary of studies on the use of Artificial intelligence in demand forecasting in metro

In recent years, the integration of artificial intelligence, advanced statistical and machine learning techniques has transformed metro transit demand forecasting leading to greater accuracy and enhanced operational efficiency in urban rail systems (Alblooshi, et.al, 2024). Contemporary research explores AI-based methodologies to improve forecasting precision. Machine learning, a sub part of AI enables where machine learning algorithms performs the task without being explicitly programmed (Nar & Arslankaya, 2022).

Celebi et. al (2009) applied neural networks to develop short-term passenger demand forecasting models to be used in the operational management of light rail services. Similarly, Nar & Arslankaya (2022) employed a hybrid approach combining regression analysis with machine learning algorithms, including artificial neural network to forecast passenger demand. Their study addressed demand prediction on both line and station levels, demonstrating the effectiveness of multiple techniques.

In the context of Thailand's Metropolitan Rail Transit Purple Line, Kusonkhum et. al. (2022) examined several machine learning algorithms such as artificial neural networks, random forests, and decision trees for demand forecasting. Their comparative analysis revealed that the artificial neural network model outperformed the others predictive accuracy, making it the most suitable for forecasting passenger demand on that rail line.

Ding et al. (2024) addressed the challenges of station level metro ridership prediction under expansion scenarios. They proposed a Metro-specific Multi-Graph Attention Network to predict long-term station level ridership during network expansion planning using data from Shanghai Metro, China.

Feng et al. (2021) proposed an improved Wasserstein Generative Adversarial Network (WGAN) model, a type of deep learning model for railway passenger demand forecasting using web search terms data. The improved WGAN model can generate virtual data to expand real dataset and predict demand more effectively, testing in Beijing revealed that changes in the web search behaviour precede changes in railway demand by about one month making it useful for early forecasting.

Gwon et al., (2024) focused on short-medium demand forecasting, the study presented a model for predicting hourly subway ridership based on weather conditions using three artificial intelligence algorithms, multiple linear regression (MLR), Random Forest regression (RFR) and Multi-Layer Protection (MLP) and it showed the model outperformed the alternative models in accurately predicting subway ridership.

Table 7: Summary of research on the use of AI for Demand Forecasting in Metro Operations (Source: AU 2025)

Study	**Model/Method**	**AI tool**	**Main Innovation**	**Time Horizon**
Celebi et al. (2009)	Neural Networks	Deep learning	Neural networks for short-term passenger demand	Short-term
Nar & Arslankaya (2022)	Hybrid Regression + ANN	Machine Learning	Combining regression and ANN for station/line demand forecasting	Short-term
Kusonkhum et al. (2022)	ANN, Random Forest, Decision Tree	Machine learning	Comparative analysis of ML methods; ANN best	Short-term
Ding et al. (2024)	Metro-MGAT	Deep Learning (Graph-based)	Long-term ridership forecasting under expansion scenarios	Long -term

Study	Model/Method	AI tool	Main Innovation	Time Horizon
Feng et al. (2021)	Improved WGAN	Deep Learning (GAN)	Forecasting railway demand using web search terms	Short to Medium-term
Gwon et al (2024)	MLR, RFR, MLP Comparison	Machine Learning	Predicting subway ridership with weather influence	Short to Medium-term

In conclusion, although the body of research applying AI to passenger demand forecasting is still evolving, there is a clear and growing interest in leveraging deep learning and advanced machine learning techniques to overcome the limitations of traditional models.

4.2.4 SUMMARY

To conclude, traditional statistical forecasting models such as ARIMA and regression-based approaches have proven effective for short- to medium-term passenger demand forecasting when historical data is readily available. However, these methods face clear limitations in scenarios involving network expansion, where future stations lack historical ridership records. In contrast, recent advances in artificial intelligence and machine learning offer a powerful and promising alternative. AI-based models, particularly those leveraging deep learning and graph-based techniques, demonstrate strong potential to address the inherent complexities of demand forecasting in data-scarce and dynamically evolving transit systems. This emerging shift marks a significant step toward more adaptive, data-informed, and forward-looking urban transportation planning.

4.3 TIMETABLE CREATION SUPPORT USING GTFS FEEDS

4.3.1 BACKGROUND

Timetable creation is undoubtedly a key component of metro operations, which has a direct influence on service performance, passenger satisfaction and is the backbone of a successful metro service. To balance operational limitations with varying demand, timetable creation has historically depended on manual modifications and heuristic approaches. However, as transit and timetabling data has become more widely available and more accessible, experts are looking into data-driven approaches to improve service reliability and timetable efficiency. General Transit Feed Specification (GTFS) has become the backbone of timetabling, providing a valuable dataset for optimising, analysing as well as automating timetable creation. The current body of research on timetable creation using GTFS is examined in literature review, looking in further detail at tactical planning as well as frequency of service.

GTFS is a standardised data format that provides a structure for public transit agencies to describe the details of their services such as schedules, stops, fares, etc (GTFS, 2025). Consequently, GTFS enables public transit agencies and operators to publish data within a format that is compatible with a significant amount of software programs, including trip planners, e.g. Google Maps. Therefore, this allows passengers to use their mobile devices (e.g. smart phones and tablets) to quickly obtain transport information. GTFS has two main parts, GTFS Schedule and GTFS Realtime. GTFS Schedule provides basic static transit information such as routes, schedules and fares in simple text format for easy creation and maintenance. GTFS Realtime contains more dynamic information such as trip updates and service alerts, which can work in conjunction with GTFS Schedule to inform transit users and operators of service disruptions and updated arrival times. It has been increasingly being used to optimise transit services.

4.3.2 OVERVIEW OF TIMETABLE CREATION USING GTFS FEEDS

A significant advantage of GTFS data is the versatility, Antrim and Barbeau (2013) illustrate the diverse applications of GTFS data, highlighting its versatility and ability to enhance public transport information. They explore how GTFS data facilitates journey planning, real-time departure information, accessibility for passengers with reduced mobility as well as providing data to facilitate research in transportation planning. Additionally, the report discusses how GTFS can facilitate open data platforms, third-party applications and interaction with other mobility services to foster innovation and accessibility. There are plenty of opportunities available for transit and intermodal operators and stakeholders to leverage open GTFS data and offer a wide range of new information services to the public or their internal operations at minimal or no expense to the organisation. To conclude, the study emphasises how crucial and valuable GTFS is to improve the effectiveness, accessibility, and user experience of public transit. Whilst the versatility and accessibility of GTFS data is clear, Wessel and Farber (2019) analyse the accuracy of schedule-based GTFS data in measuring accessibility, specifically how it compares to real-life departure times. Later examining how GTFS estimated times can vary from actual departure times due to service disruption and variation in transit operations. Interestingly, the study highlights the limitations of relying solely on static GTFS data because it has been found that it potentially overestimates reliability as it assumes all services adhere to the schedule. Wessel and Farber therefore theorised that by combining both static GTFS data and real-time information, this would lead to more accurate transport information. Overall, this study found that greater research is required to fully comprehend the unpredictability and diversity of transit travel. Except in extremely basic situations or in situations where schedule adherence is known to be exceptional, schedule data alone might not be enough to show how access varies over time across transit networks. Understanding how transit travel time variability is seen as a quasi-stochastic phenomenon and utilised to guide itinerary planning, mode selection, and route selection is necessary.

Furthermore, another significant benefit for the use of GTFS data in timetable creation is the strategic advantages to future timetables and research. Aemmer, Ranjbari and MacKenzie (2022) illustrate that in addition to facilitating faster, safer, and more efficient travel for users, timely, transparent, and trustworthy public timetable data also opens research opportunities that can aid with better planning and service delivery. They highlight how gaps still exist in the UK despite continuous attempts, impeding the progress of the previously indicated advantages. These shortcomings make the UK transport system less resilient, restrict research opportunities, and put the country at a competitive disadvantage internationally. The advantages of adopting an integrated data management perspective are illustrated by international best practices in the US and Europe, which offer examples of how comparable problems might be resolved. A UK-wide integrated public transport open-data program that emphasises data governance, consistent data formats, and stakeholder involvement is strongly recommended. In addition, it is crucial to make historical data accessible, work towards data standards strategically, and support operator and stakeholder skill development.

Illustrating the clear advantages of GTFS data, McHugh (2013), illustrates how the most significant advantage is the global reach of GTFS standard information, therefore, this allows for products and information to be acquired by millions of people daily. Furthermore, for potential passengers who are unfamiliar with a city or region, passengers can be provided with information easily, because of GTFS data, through a familiar interface and can find alternative modes to driving with ease. The author highlights that by providing enhanced and easy to recognise information, this improves service delivery for the citizens of a respective city or region, all at a low cost for the local government and operators. However, Newmark (2024) mentions that the benefits of GTFS data are only “dependent on the underlying quality of the data.” Within the literature, Newmark evaluates the quality of GTFS data, which is essential for many service timetabling and information systems. Interestingly, Although GTFS has been widely used, it is apparent that little study has been done on methods to evaluate its accuracy. To address this, Newmark presents a variety of methods and metrics to assess and analyse both the temporal accuracy and spatial accuracy of both GTFS Realtime feeds and GTFS schedule feeds. The metrics were developed to provide public transport operators and organisations a clear insight into the quality of the information they supply to their passengers and wider stakeholders, specifically highlighting the significance of the inaccuracies on customer satisfaction. To assist transport operators and travel organisations, the metrics that were set out within the report, will allow operators to constantly analyse the accuracy of the information and GTFS data provided to their passengers.

Presenting an interesting perspective into timetabling, Sun et. al. (2014), looking at Demand Responsive Services illustrate three models to design demand-responsive timetables for metro services, using data gathered from smart-cards to achieve a greater understanding of spatial-temporal passenger demand. As a result, timetables created that are demand-sensitive are advantageous to reducing passenger cost. The research presents that the reliability of the metro service depends on the design of the timetable. A typical timetable, based on peak and off-peak demand, is a simple and widely used approach in day-to-day service operations. Train overcrowding and lengthy station wait times could come from such a strategy's inability to satisfy dynamic temporal passenger demand. A significant development is the introduction of smart cards and their ability to illustrate temporal and spatial demand on a detailed level across an entire network. Consequently, Sun et. al. (2014) proposes three differing models to optimise and design demand sensitive timetables. The first model seeks to ensure the timetable is more dynamic, the second model focuses on capacity constraints, extending where necessary and the third model aspires to design a demand-sensitive peak and off-peak timetable with capacity constraints considered. These three models were tested on the Singaporean Metro, the three models were evaluated and analysed against a plethora of varying parameters. Following the testing of the models it was found that the capacitated model illustrated the best performance whilst under fixed capacity constraints, however, the uncapacitated model provided optimised rolling stock configurations depending on the time. Finally, the peak and off-peak model provided lower performance, it is much simpler to operate from an operator’s perspective and easier to understand for passengers, as opposed to the utilisation of dynamic headways.

Regarding transit within city centres, traffic signals can understandably cause inaccuracies in GTFS real-time data, as delays cannot be predicted whilst waiting for signals to clear. A strategy to resolve this is transit signal priority, this is highlighted by Zhou et. al. (2024), signals will recognise transit and attempt to reduce the waiting time, consequently, benefitting the reliability of the service and of the real-time data. The major obstacle regarding the deployment of GTFS-based TSP in GTFS-Real-time is latency. To address this, the study analysed data from 4 transport operators to identify the problems with late data. Experimental findings show that two machine learning models outperform the baseline strategy, which uses hourly averages for dwell times and vehicle speeds. By addressing several problems with the available GTFS data, this paper improves the viability and usefulness of GTFS-based adaptive TSP. This study stresses bus location estimation and offers a practical way to adjust for latency and enhance bus location and dwell time estimation, in contrast to traditional methods that concentrate on bus arrival time estimation.

Finally, to give an overview, Fan and Li (2019) highlight that the emergence and evolution of GTFS being an open standard format has created a plethora of opportunities for assessment, benchmarking, research and to monitor service performance. The contents of GTFS data, consisting of both temporal and spatial aspects, this standard transit feed data format has proven to be quite valuable. Studies that combine those two, however, are still making only moderate and gradual progress. More spatially disaggregated, personalised, and time-aware accessibility measurements are needed to enhance these studies, as are more advanced spatial computational methods to operationalise these metrics and enhance the measurement of equity and transit accessibility in empirical research.

To conclude, the literature reviewed in this section present a clear overview of the benefits and some drawbacks regarding GTFS data. As the literature illustrates, a clear advantage for operators and agencies for using GTFS feeds is the versatility, foundation for research and strategic planning, ease of access and opportunities for monitoring performance. Whilst, on the other hand, ensuring data is of high quality is important, the benefits of GTFS data, has allowed academics, agencies and operators to plan timetables strategically and tactically, improving service delivery for passengers. A significant trend across the literature is the versatility of GTFS data, to allow for future research and development of new timetables.

4.3.3 TACTICAL PLANNING USING GTFS DATA

Looking in greater detail at tactical planning, across all modes of transportation, services are susceptible to uncertainties that can disrupt train services, delay numerous trains, and spread throughout the network, even with the most advanced communication, monitoring, and control systems. Coviello et. al. (2023) illustrate that; “Strategic planning is critical in helping railways develop optimal programs for improving their business by making service more attractive and efficient.” As a result, the advantages of tactical planning are clear for operating reliable and resilient metro services, the data presented by GTFS feeds can provide in-depth analytics for timetable planners, highlighting key locations across the network as to where disruption can occur.

Bouman (2022) criticises the conventional method of allocating buffer times using predetermined, set values, illustrating that it limits operational capacity but also, necessitates timetable planners input to modify the timetable. Consequently, she presents a data-driven approach for creating tactical planning guidelines for buffer times that can be used while creating the original schedule. This method predicts mean secondary delay and hindrance percentage, two important measures of delay propagation, using multiple linear regression analysis. To test the methodology, Bouman used analysed the Dutch rail network on services between Haarlem, Leiden Central and Schiphol Airport. The investigation showed that the selected timetable characteristics may be used to forecast the mean secondary delay and hindrance percentage with an accuracy of 90.7%. Interestingly, the impediment percentage exhibited a considerable correlation with the scheduled buffer time, although the mean secondary delay was not significantly affected by it. This suggests that by properly allocating buffer hours, trains are less likely to impede one another, improving timetable stability overall. Therefore, by tactically planning a timetable with effective headways, service reliability and performance can be maintained and improved.

Looking at a metro perspective Torres (2024) addresses the challenges of tactically planning and the synchronisation of timetable creation, with a focus on the Porto Metro. Torres suggests that differing types of rolling stock and varying passenger demand are the two significant barriers to a successfully synchronised timetable. Consequently, to address the barriers, Torres provides a modelling framework that considers the factors to improve the reliability and efficiency of the timetable. Presenting a data-driven approach for the creation of synchronised timetables that take into account varying passenger demand and a variety of vehicle types. The model incorporates the prioritisation of long-distance connections whilst ensuring better services within peripheral areas. To test the methodology, Torres employed six measures, including two manually determined bunching indicators, the study then compares the optimised timetables with current schedules placed under various scenarios to assess the model. The outcomes show notable gains in synchronisation despite technological challenges and iterative modifications. It was important to note however that whilst the models have minimised the bunching of services, it was not eliminated.

Furthermore, Schettini, Jabali and Malucelli (2022), discuss how to better coordinate the operations of metro lines with fluctuating passenger demand. Typically, metro operators employ headways between services, however, this may not effectively handle changing passenger demand patterns. Therefore, the study proposes a demand-driven timetabling strategy which is designed to allow trains to operate without a concrete timetable. Features such of short turning, allowing trains to reverse prior to reaching the terminus of the line is a crucial component of this approach. The study created a mixed-integer linear programming model specifically designed for a bidirectional metro route to test this method in practice. Presenting an explicit approach that makes use of cut generation techniques and two classes of valid inequalities, they significantly improve computing efficiency. Computational experiments on both simulated and real-world metro lines are used to assess the methodology. To conclude, the outcomes show how well the suggested algorithm works and emphasise the advantages of the demand-driven timetabling approach, especially in terms of cutting down on passenger wait times.

Undoubtedly, one of the most significant performance metrics in public transport operations is reliability. Van Oort and van Nes (2008) highlight that there is a plethora of factors that contribute to delays within an urban environment, as a result, causing extended waiting times for passengers. It is illustrated that due to the short nature of journeys within metropolitan areas, passenger waiting times have significantly increased in metropolitan areas due to service unreliability. In addition to extended journey and wait times, services can bunch as a result, consequently, reducing comfort and decreases the likelihood of passengers finding a seat. Similarly, tourists may be unsettled by the uncertainty around the reliability of transport. As a result, the study hypothesises that "during the strategic and tactical planning phases reliability can be taken into account and be improved." To assess the impact of unreliability of services on passengers, a case study of the tram network in The Hague, is used to better comprehend the components behind the unreliability. Following the collection of data, an analysis of the components of real trip time is conducted. Latterly, solutions are proposed and examined. It has been demonstrated that travellers experience less additional waiting time when different parameter values are used in timetable preparation than are currently utilised. Additionally, the impact of explicitly considering reliability in the design of line length, stop spacing, and coordination mechanisms is examined. Overall, the study demonstrates that reliability improvements can be already achieved during the planning phases of timetabling.

Furthermore, Bešinović et. al. (2021) examines current advancements in railway timetabling. To fully utilise advanced railway systems and offer more capacity, as well as more sustainable, resilient and efficient services both under normal circumstances and during disruptive occurrences. Demonstrating the necessity of mathematical models and sophisticated timetabling modelling and analytics. Timetabling approaches are presented in the study according to their amount of complexity, performance goals and planning phases, ranging from strategic to near real-time. The study reports that most research has concentrated on enhancing efficiency and robustness, with only limited consideration regarding resilience. As well as focused mostly on timetable creation, with little attention paid to timetable modifications. The report assists future research in identifying current and emerging patterns and innovative timetabling strategies. Enhancing this by providing real-world implementation examples and practical considerations, to illustrate the benefits of greater, more advanced timetable planning. The study is of significant value to timetable planners, giving an overview of areas that are frequently overlooked.

Overall, tactical planning can significantly enhance timetables both in terms of reliability and resilience. Across the literature a key trend is that reliability and performance improvements can be made through tactical planning, examining headways, demand-responsive approaches, reliability enhancements and innovative timetabling strategies. As GTFS offers standardised, machine-readable transit data, GTFS feeds are essential for conducting in-depth analyses of the current timetable and operation. Operators can use this to highlight any inefficiencies, analyse various scenarios, and adapt the timetable, which directly increases network resilience and timetable dependability by utilising GTFS data. Additionally, GTFS feeds simplify the incorporation of real-time data, which supports more flexible and responsive network planning and resilience.

4.3.4 GTFS DATA ENHANCING FREQUENCY OF SERVICE

A further area of analysis is regarding Frequency of Service, analysing frequency using GTFS feeds. The literature highlights that tools are available for operators to use, utilising GTFS data to enhance timetables and set an optimal frequency. Finally, to enhance frequency, decision-making by service controllers needs to be optimised, utilising key strategies such as short-turning, express running and bunching to provide the optimal frequency for passengers.

A significant aspect of passenger experience is waiting times, Canavan et. al. (2019) illustrates that many metro networks across the globe are facing increasing demand and will need to provide more capacity in strategic corridors. To alleviate this, the predominant strategy to boost capacity on existing lines with fixed infrastructure is to increase frequency. By carrying more passengers as well as faster journey times, higher frequencies can also improve efficiency by maximising the use of rail infrastructure, boosting operator revenues, as well as, providing broader economic advantages to the cities they serve. The study goes on to review a community of metro operators across 17 high frequency lines, this being classified as having at least 25 trains per hour. The paper then illustrates the various constraints to high frequency operation, being categorised into five types; "relating to signalling and train control, station and train crowding, fleet, terminal turnarounds, and service complexity." Following this, solutions to mitigate these issues are presented, highlighting that metro operators must adopt a comprehensive strategy to attain the highest frequencies. It is important that operators identify all the constraints that can prevent the full benefits of high frequency operation, all primary, secondary and tertiary constraints. Finally, the paper provides guidance as to how to maximise frequency, consequently, delivering benefits to passengers, agencies and wider stakeholders.

Presenting a recent perspective that has affected all operators globally, Gkiotsalitis and Cats (2022) portrays how the impact of the COVID-19 pandemic had on the public transport sector. Following the restrictions across countries, ridership declines of up to 90% were noted in some regions. As a consequence, public transport operators had to urgently respond to how restrictions and social distancing policies affected daily operations and passenger experience. The paper evaluates the consequences of a plethora of social distancing policies, presenting a model for redesigning public transport services meanwhile, taking operational, passenger and revenue loss-related costs into account. The methodology provides the optimal vehicle redistribution across the network for various social distancing circumstances, the paper portrays that for metro networks recovering and adapting following the COVID-19 pandemic, governing bodies and operators can utilise the model and findings as a tool to assist their own networks.

The impact of service control decisions on high-frequency metro lines service performance and reliability is examined by Carrel et. al. (2010). The report examines the operational choices made by controllers, such as holding, expressing, or cutting trains short, and assesses the effects these choices have on passenger satisfaction and service reliability. The identification of shortfalls in previous research is highlighted and the paper proposes a framework to mitigate some of the shortfalls identified. A significant element of the framework is the description of the environment in which decisions are made within an operations control centre. A plethora of endogenous aspects are highlighted that influence the reliability of the system, found by the research completed by visiting controls centres. Furthermore, the management of personnel and rolling stock, safety, and infrastructural capacity are important factors that are considered by controllers and decision makers in operation control centres, as well as, maintaining adequate service levels to minimise disruption to passengers. Consequently, the paper found that operations controllers had a strong preference for manageable and robust control strategies, as a result of the uncertain environment in which the control centre functions. In order to prove this, a case study was presented where controllers had to respond to two comparable incidents, using distinct recovery tactics, primarily due to crew management concerns, demonstrating how crucial it is that there is a thorough grasp of the objectives and limitations service controllers encounter on a regular basis.

Overall, throughout the literature, there are several key points to highlight how service frequencies can be enhanced. Operators should identify the constraints that can prevent high frequency operation, as well as leveraging models to assist with strategic planning to enhance services. To achieve this, GTFS data is crucial, as it provides a standardised framework for the analysis of the current timetable, service patterns and vehicle data. GTFS data can allow operators to simulate potential changes to services, including increasing frequency. Furthermore, the training of service controllers should be thorough, ensuring that the GTFS-derived insights can be applied, so that the full potential of the network can be achieved, whilst minimising disruption to passengers.

4.3.5 SUMMARY

To conclude this literature review recent studies now emphasise how crucial data-driven strategies are becoming in transit planning. The benefits and versatility of GTFS data is clear, yet there is still more research and advancements possible. Delay mitigation in urban environments that hinder the reliability of the data is a significant area for future research and development. As well as this, operators and agencies must ensure that the data provided is of high quality with frequent assessment to maintain its quality and reliability. Furthermore, both tactical planning and frequency of service are two significant areas that must be considered when creating timetables. Tactical planning can vastly improve schedules in terms of robustness and dependability. A major theme in the literature is that strategic timetabling methods and reliability enhancements can all lead to increases in performance and dependability. Overall, there is literature that show how frequencies may be enhanced. To improve services, operators should use models to help with strategic planning and identify any limitations that would hinder high frequency operation. In order to maximise the network's capabilities and minimise passenger disruption, service controllers need also receive extensive training. With research and studies progressing within this field constantly, new data and the evolution of artificial intelligence will transform how timetables are created in the future.

4.4 ANOMALY DETECTION

4.4.1 BACKGROUND

Recent methods for unsupervised and weakly supervised anomaly detection in surveillance video have achieved high accuracy by combining robust feature extraction, memory-augmented reconstruction, and multiple-instance learning frameworks. The deep multiple-instance ranking approach of Sultani et al. demonstrated that MIL-based video-level supervision can effectively learn to identify anomalous segments in complex scenes, including violence and unattended objects. Building on this, Robust Temporal Feature Magnitude learning enhances the discrimination of abnormal patterns by adjusting temporal feature magnitudes during training to reduce false positives from normal video segments (s Tian, Y., et al. (2021). Memory-guided Normality frameworks employ an external memory module to model diverse normal behaviours and detect deviations via reconstruction errors, proving effective in crowded or dynamic environments such as metro stations. Complementary approaches use adversarial background-agnostic training to improve robustness to scene variations and lighting changes common in transit hubs. There also exist more recent approaches like Transformer-based attention models extract long-range temporal dependencies and capture complex interactions among individuals, supporting accurate crowding and aggression detection.

Multimodal fusion architectures like CFA-HLGAtt leverage audio and visual streams to detect disruptive events, including loud disturbances or altercations that may go unnoticed in visual-only systems (Wu, P., et al. 2020). Graph convolutional noise-cleaner modules refine frame-level predictions by mitigating label noise, which is valuable when curating large, unlabelled surveillance datasets. Together with efficient autoencoder variants—such as ADNet with temporal consistency regularization—these methods can be deployed to monitor crowded platforms, flag abandoned luggage via motion saliency, and alert operators to aggressive behaviours in real time. By successfully integrating a selection of state-of-the-art anomaly detectors into existing CCTV infrastructure, we think that systems supporting metro operations can achieve improved situational awareness and incident response using a combination or adaptations of these already existing techniques.

4.4.2 UNCLEANLINESS DETECTION IN VEHICLE INTERIOR

Detecting uncleanliness in metro environments represents a classic computer-vision challenge: the system must reliably distinguish between normal station fixtures and unexpected contaminants—litter, spills, graffiti—under widely varying lighting and occlusion conditions. We view this as an image-classification and object-localization problem on individually selected frames of CCTV footage, to be considered in addition to the anomaly detection tasks on that same video footage. By treating each video frame as an independent still image, we can deploy high-throughput pipelines extracting frames at fixed intervals or based on some detected parameters like the amount of occlusion, running them through a detector, and flagging regions that deviate from learned "clean" baselines. This per-frame approach simplifies data requirements, avoids the expense of processing all video data, and still delivers low-latency alerts suitable for real-time cleaning dispatch. Subsequent sections will describe methods and strategies suitable for this problem.

4.4.2.1 CONVOLUTIONAL NEURAL NETWORKS

Convolutional Neural Networks (CNNs) are the core building blocks of many state-of-the-art vision models and convolutional layers are the core building blocks of CNNs (O'Shea, K., & Nash, R., 2015). A convolutional layer applies a set of learnable kernels (filters) across the spatial dimensions of its input—typically a three-dimensional tensor of shape (height, width, channels)—to produce a stack of feature maps (Figure 7).

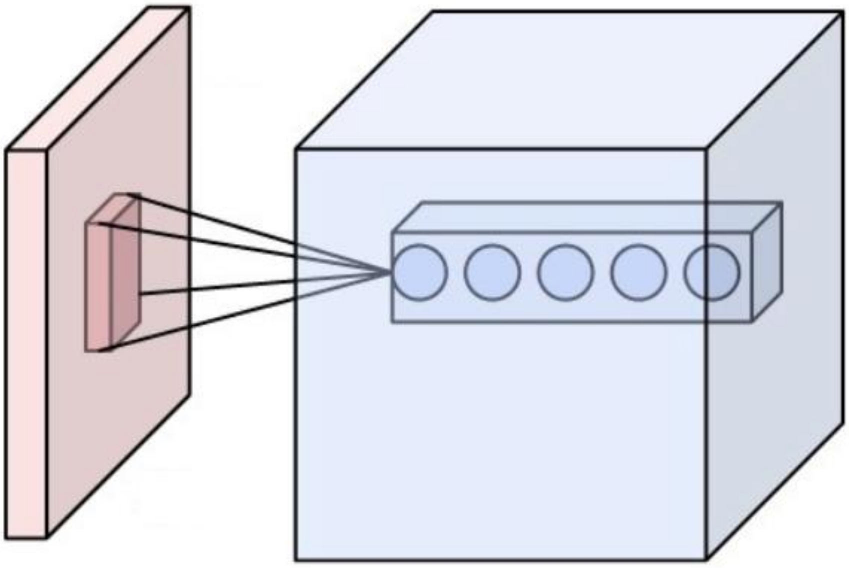

Figure 7: Convolutional Layer (Source: Wikimedia Conv layer.png 2025)

Each kernel is a small tensor whose weights are shared at every spatial location: during the forward pass, the kernel is slid across the input in strides of one or more pixels, computing at each position the dot product between the kernel's weights and the corresponding input patch (plus an optional bias), thereby encoding local patterns such as edges or textures.

Multiple kernels yield multiple output channels, with the idea that each can detect a different learned feature. By adding additional layers (Figure 8) increasingly abstract, hierarchical features are learned.

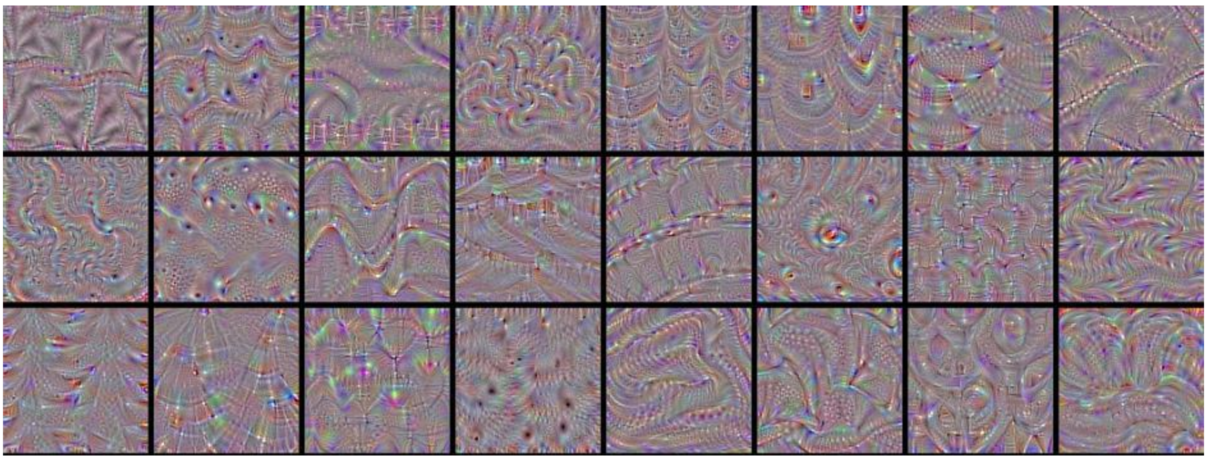

Figure 8: Layer Visualization (Source: Chollet F. 2016)

4.4.2.2 RESIDUAL NEURAL NETWORKS

Residual Neural Network (ResNet) is a convolutional architecture that introduced residual learning to ease training of very deep networks by reformulating each stack of layers as a residual function $F(x)+x$, adding the layers input to its output, enabling the successful training of hundreds of layers without degradation of accuracy. Each residual block comprises two or three convolutional layers with BatchNorm and ReLU activations, coupled with an identity “skip” connection that preserves gradient flow during backpropagation and mitigates vanishing gradients (He, K., Zhang, X., Ren, S., & Sun, J. 2015). Models such as ResNet-50 pretrained on ImageNet provide rich feature extractors whose final fully connected layers can be replaced and fine-tuned for downstream tasks, producing hierarchically organized feature maps that capture edges, textures, and object-part patterns useful for discerning clean versus soiled surfaces. For uncleanliness classification in metro operations, the pretrained ResNet backbone’s last pooling output is fed into a new binary classifier head trained on labelled examples of litter, spills, stains, etc., allowing the network to learn grime-specific decision boundaries while leveraging the backbone’s general visual features. During fine-tuning, one typically freezes early layers to retain generic features and updates only the deeper layers or added classifier with a low learning rate, reducing overfitting when data are limited. At inference, each station image or video frame passes through the network at real-time speeds, with the SoftMax output yielding a probability of uncleanliness that can trigger automated alerts to direct personnel precisely where needed and possibly provide them with the image so they can judge the situation.

4.4.2.3 YOU ONLY LOOK ONCE ARCHITECTURE

You Only Look Once (YOLO) is a one-stage, grid-based object detector introduced by Redmon et al. in 2015 that frames detection as a regression problem, dividing the image into cells and using a single convolutional network to predict bounding boxes and class probabilities in one forward pass. It employs a backbone–neck–head pipeline to extract multi-scale feature maps, alternating convolutional layers and batch normalization to achieve real-time speeds. The architecture has seen huge improvements in the last decade (e.g. Khanam, R., & Hussain, M., 2024), with the most recent iteration YOLOv11 advancing this architecture with a refined CSP-based backbone and enhanced neck for richer feature extraction, an anchor-free head that predicts the centre of objects directly, and optimized training pipelines for improved accuracy and throughput. For uncleanliness detection in metro stations, we will also attempt to fine-tune the pretrained YOLOv11 model on a curated dataset of litter, spills, stains, etc. by retraining the lightweight detection head on these objects while leveraging the existing backbone feature extractor. Deployed on live CCTV feeds, the model should flag any such irregularities so they can be raised with personnel, providing them with the image of the issue and the precise locations in real time.

4.4.2.4 GENERALIZATION, FEATURE MAPS, TRANSFER LEARNING AND FEW/ZERO SHOT LEARNING

Generalization in deep learning hinges on a model’s ability to perform well on data beyond the examples it saw during training, and convolutional feature maps lie at the heart of this capability. As an input image propagates through successive convolutional layers, each layer’s kernels extract increasingly abstract representations: early layers detect simple edges and colour gradients, intermediate layers capture textures and motifs, and deeper layers respond to object parts or even entire object prototypes

(Wang, M., & Deng, W., 2018). These hierarchically organized feature maps serve as a rich, multi-scale basis for recognizing patterns in novel inputs, enabling the network to generalize from limited examples. Transfer learning leverages this property by decoupling the feature extractor—typically a deep backbone pretrained on a large dataset such as ImageNet—from task-specific heads (Figure 9).

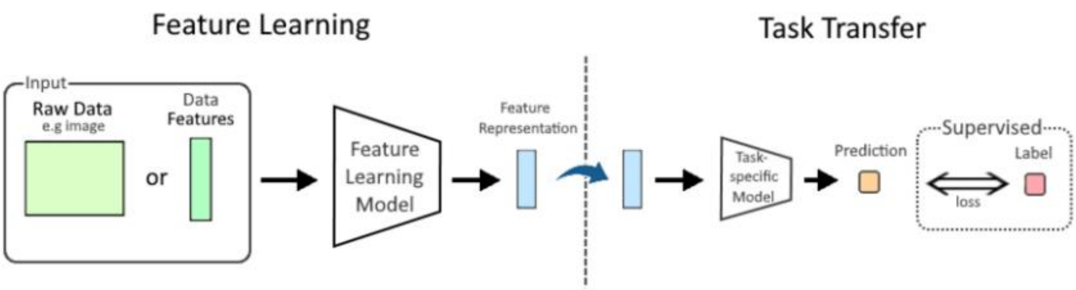

Figure 9: Feature Learning Diagram (Source: Wikimedia Feature Learning Diagram 2025)

By freezing or lightly fine-tuning the backbone's weights, one can train new classifiers, regressors, or detectors atop its output feature maps using far less data and compute than training end to end. In practice, the pretrained feature extractor provides a stable embedding space in which new tasks' decision boundaries can be learned with minimal overfitting. Building on transfer learning, few-shot and zero-shot learning seek to minimize or eliminate the need for labelled examples of novel classes. The robustness and richness of the backbone's convolutional feature maps determine how well the model can bridge from seen to unseen concepts. Consequently, designing and training backbones for maximal generalization—through data augmentation, architectural choices that promote spatial invariance, and objectives that encourage disentangled representations—directly enhances performance in transfer, few-shot, and zero-shot settings. Features learned once can serve as a universal perceptual substrate for a wide array of downstream tasks, reducing the data and annotation requirements for training computer vision models on new tasks and classes using existing backbones, like that of the aforementioned YOLO models.

5 NEXUS DATA SCIENCE AND AI USE-CASE CONCEPTS

Metro stations and the trains themselves employ a great number of CCTV and surveillance cameras. Traditionally, they are monitored by human workers directly, however advances in Computer Vision over the past decade offer many opportunities to add automated image and video processing to this data, to offer gains in efficiency or an increase of service quality in terms of response times or error rates.

In addition to video and audio feeds of CCTV cameras, modern metro systems generate a wealth of other data streams: passenger flow and journey records from ticketing and turnstile systems, GPS, signalling, and train telemetry data, environmental and infrastructure sensors (e.g., vibration, temperature, air quality); Wi-Fi, Bluetooth, and mobile-app interactions for real-time crowd density estimates; and maintenance logs from IoT-enabled equipment. In the following we discuss the use-cases we identified together with metro operators present at the General Assembly meeting in Vienna and methods that could assist in these issues:

- Predictive maintenance to extend asset lifespan while boosting maintenance efficiency and quality.
- AI-driven knowledge management for internal procedures, enabling fast retrieval of security and safety protocols for specific tasks or entering an area.
- Crowd forecasting and management, leveraging past event data to predict attendance for recurring events, anticipate first-time event crowds, model their likely routes, and provision extra services.
- Real-time passenger assistance in native languages, guiding travellers through the network, alerting them to service outages, and suggesting alternative routes—especially valuable during major events.
- Automated security monitoring, including detection of suspicious or abandoned objects (e.g., luggage) and continuous aggression/suspicious-behaviour surveillance.
- Sanitary monitoring, spotting uncleanliness issues in real time to prompt targeted cleaning rather than broad end-of-line sweeps.
- Dynamic automated train operation, adjusting speeds to conserve power and delaying station entry when no passengers are waiting in a high-frequency metro system, or dynamically add or remove trains from circulation based on demand.
- Belongings tracking to identify pickpocketing incidents and match found items with their owners for efficient lost-and-found management.

Based on our conversations with metro operators and our continued research and experience of the industry partners in the project, we focus our work on use-cases that are both being requested by operators and have a high probability of yielding positive outcomes within the scope of this project.

5.1 PREDICTION OF CROWDING BASED ON EXOGENOUS DATA SOURCES

Genoa's metro system, managed by the Azienda Mobilità e Trasporti (AMT[1]), forms a critical component of the city's urban public transport network. The system, which runs along a striking northwest-to-southeast axis across the city, is anchored by a single, yet strategically important, line that stretches 7.1 kilometres. Originally launched in 1990, this line has evolved with several phased extensions, now connecting key urban and suburban areas while addressing growing transportation demands. By linking the suburban area of Brin in the Rivarolo district with Piazza Principe and Brignole —the two Genoa's major railway stations— the metro not only caters to daily commuters but also supports regional mobility.

5.1.1 GENOA METRO SYSTEM DESCRIPTION

At its core, the Genoa metro is designed as a double-track system. This configuration facilitates the smooth operation of trains running in opposite directions on parallel routes, ensuring an efficient distribution of passenger traffic. With eight strategically located stations (s. Figure 10), the metro line is engineered to serve Genoa's diverse urban landscape. Each stop has been carefully positioned to maximize accessibility to residential, commercial, and tourist zones:

- **Brin Station:** Serving as the northwestern terminus, Brin is situated in the Certosa district. It is an essential node for residents in suburban neighbourhoods and provides a gateway into the metro network.
- **Dinegro Station:** This station is positioned in proximity to the maritime station and the passenger port, making it a vital access point for maritime commuters and workers involved in port activities.
- **Principe Station:** Beyond providing access to Genoa Principe train station—a major railway hub—this station plays a crucial role in intermodal connectivity, linking the metro with national and regional rail services.
- **Darsena Station:** Located adjacent to the port area and the historic centre, Darsena acts as a convenient stop for both residents and tourists who wish to explore Genoa's heritage sites.
- **San Giorgio Station:** Found near the renowned Genoa Aquarium and the Old Port, this stop experiences high tourist traffic and supports leisure and recreational travel.
- **Sarzano/Sant'Agostino Station:** This station caters to the university district and the surrounding historic areas, supporting both academic communities and residents of longstanding city quarters.

[1] https://www.amt.genova.it

- **De Ferrari Station:** Positioned at the heart of the city, De Ferrari is not only a hub for major office and retail complexes but also stands as a central point for administrative and business activities.
- **Brignole Station:** Marking the southeastern terminus, Brignole is strategically connected to the Genoa Brignole train station and integrates city and regional bus routes, thereby forming an integral part of the multimodal transit network.

Figure 10: Map of the Genoa subway system (Source AMT 2025)

With trains capable of reaching speeds of up to 60 kilometres per hour, the system is engineered to balance rapid transit with rigorous urban safety standards. Throughout the day, service frequencies are adjusted — typically resulting in intervals of seven to ten minutes — to accommodate fluctuating passenger volumes.

5.1.2 USE CASE DESCRIPTION

This case study sits at the intersection of the optimization activities planned in WP4 and WP6, thus ensuring synergy between the Work Packages and a concrete contribution to the overall project goals. Its integration across these packages ensures that operational innovations are not only theoretically robust but also practically viable.

5.1.2.1 SPECIFIC OBJECTIVES

A primary objective of this study is the development of an advanced predictive model tasked with estimating crowding levels at individual metro stations. By leveraging this model, urban public transport operations can benefit in several ways:

- **Operational Efficiency:** Real-time and forecasted data will allow to allocate resources more effectively, thereby reducing over-crowding and improving passenger comfort.
- **Strategic Planning:** The insights derived from predictive analytics support long-term infrastructure planning and scheduling decisions, facilitating an adaptable response to future demand surges.
- **Service Quality Improvement:** Enhanced forecasting tools enable proactive management of station occupancy, thereby improving both the safety and overall experience for commuters.

5.1.2.2 DATA SOURCES AND INTEGRATION

The predictive modelling framework is built upon a comprehensive integration of heterogeneous data sources, which include:

- **AMT Operational Data:**
  - *Metro Service Data:* This includes detailed operational parameters such as train frequency and historical crowding metrics.
  - *Surface Transportation Data:* Complementary information on bus schedules, service frequencies, and integration points with the metro network is also incorporated.
- **Exogenous Variables:**
  - *Meteorological Data:* Weather conditions, such as rainfall, temperature variations, and other environmental factors, are considered since they significantly influence passenger flow patterns.
  - *Event-Driven Data:* Detailed schedules of local special events—including concerts, sports competitions, and cultural festivals—are used to refine predictions around exceptional demand periods.

5.1.2.3 DEVELOPMENT METHODOLOGY

Data Collection and Preprocessing

The initial phase involves an exhaustive data collection process that aggregates and cleanses information from both internal AMT repositories and external datasets. Key steps in this phase include:

- **Data Aggregation:** Combining disparate data streams into a unified, accessible format.
- **Data Cleansing:** Employing imputation techniques —ranging from simple mean substitution to more advanced methods like K-Nearest Neighbours and regression-based imputation— to ensure the database is free from inconsistencies and missing entries.

- **Feature Engineering:** Developing new variables from raw data to capture temporal trends, peak-hour fluctuations, and station-specific usage patterns, which are crucial for model accuracy.

Predictive Model Development

The core of the development process hinges on deploying state-of-the-art machine learning algorithms. In this case, ensemble learning techniques such as the Random Forest algorithm are employed due to their robustness and ability to handle high-dimensional data while maintaining interpretability. The modelling process involves:

- **Hyperparameter Tuning:** Systematic exploration of algorithm parameters through grid search and cross-validation to enhance overall predictive accuracy.
- **Model Validation:** Rigorous assessment using techniques such as train-test splits and cross-validation to obtain reliable performance metrics. Key evaluation metrics include Mean Absolute Error and Mean Squared Error, which collectively offer a comprehensive view of the model's precision and reliability.

Deployment and Scalability

Upon finalizing the predictive model, the solution is deployed as an API designed with modern containerization practices. Utilizing Docker to encapsulate the application environment, the system guarantees:

- **Consistency:** Uniform performance across development, testing, and production environments.
- **Scalability:** Flexible deployment options that allow the model to be scaled according to varying operational demands without compromising stability or speed.

Reliability: Streamlined deployment and continuous monitoring ensure that the forecasting tool remains a robust asset for real-time and strategic decision-making processes.

5.2 AI AND DATA SCIENCE USE CASE FOR DEMAND FORECASTING DURING NETWORK EXPANSION IN WEST MIDLANDS METRO SERVICE, BIRMINGHAM

5.2.1 MOTIVATION

Accurately forecasting passenger demand is essential for both the operational management and long-term strategic planning of metro systems. This becomes especially critical during network expansion projects, where infrastructure investments must be aligned with projected levels of ridership. In rapidly developing urban regions such as Birmingham—a university city experiencing notable population growth and urbanisation—anticipating demand at newly constructed or soon-to-be operational metro stations is vital to ensure service efficiency and appropriate resource allocation.

Metro expansion typically involves three categories of station development: (1) new stations, which are introduced as part of the expansion; (2) updated stations, which already exist but are modified to accommodate additional lines or extensions; and (3) existing stations, which remain unchanged but may experience altered demand patterns due to network reconfiguration (Ding et al., 2024). Designing effective expansion strategies therefore requires accurate demand forecasts not only for existing infrastructure but especially for those stations that lack historical data.

Although considerable research has been conducted on demand forecasting and metro operations independently, limited attention has been paid to forecasting demand within the context of metro expansion. Most existing studies focus on short-term passenger flows such as station inflows and outflows rather than on demand forecasting that informs planning and investment decisions. Given the growing interest in applying deep learning-based methods to future urban and transportation planning, there is a compelling need to further investigate these advanced methods for planning metro systems of the future.

5.2.2 PROBLEM DEFINITION CASE STUDY – WEST MIDLANDS METRO

Population and economic growth are among the principal drivers of metro expansion in the West Midlands region (Pugh & Stubs, 2024). As part of its broader urban development strategy, the West Midlands Combined Authority is actively pursuing the development of a more integrated transport system that leverages existing rail, tram, and road networks. The West Midlands Metro, originally established in 1872 and later revived in 1999, plays a central role in this vision.

The current metro tram line connects Birmingham New Street station with Wolverhampton St George's, having been extended in 2015 to link Snow Hill station with the Birmingham city centre shopping district and Grand Central station. Since 2019, additional expansions have been underway, with the goal of completing all planned works by 2026 as shown in the extension map in Figure 11 below. These include new lines and stations to support growing demand, particularly in areas undergoing significant residential and commercial development (Metro Alliance, 2023).

However, predicting passenger demand at newly added stations presents a major challenge, as no historical ridership data exists for these locations. Additionally, the interdependencies between evolving urban characteristics and future demand patterns must be considered. This case study proposes the use of AI to address these complexities and improve demand forecasting during metro expansion.

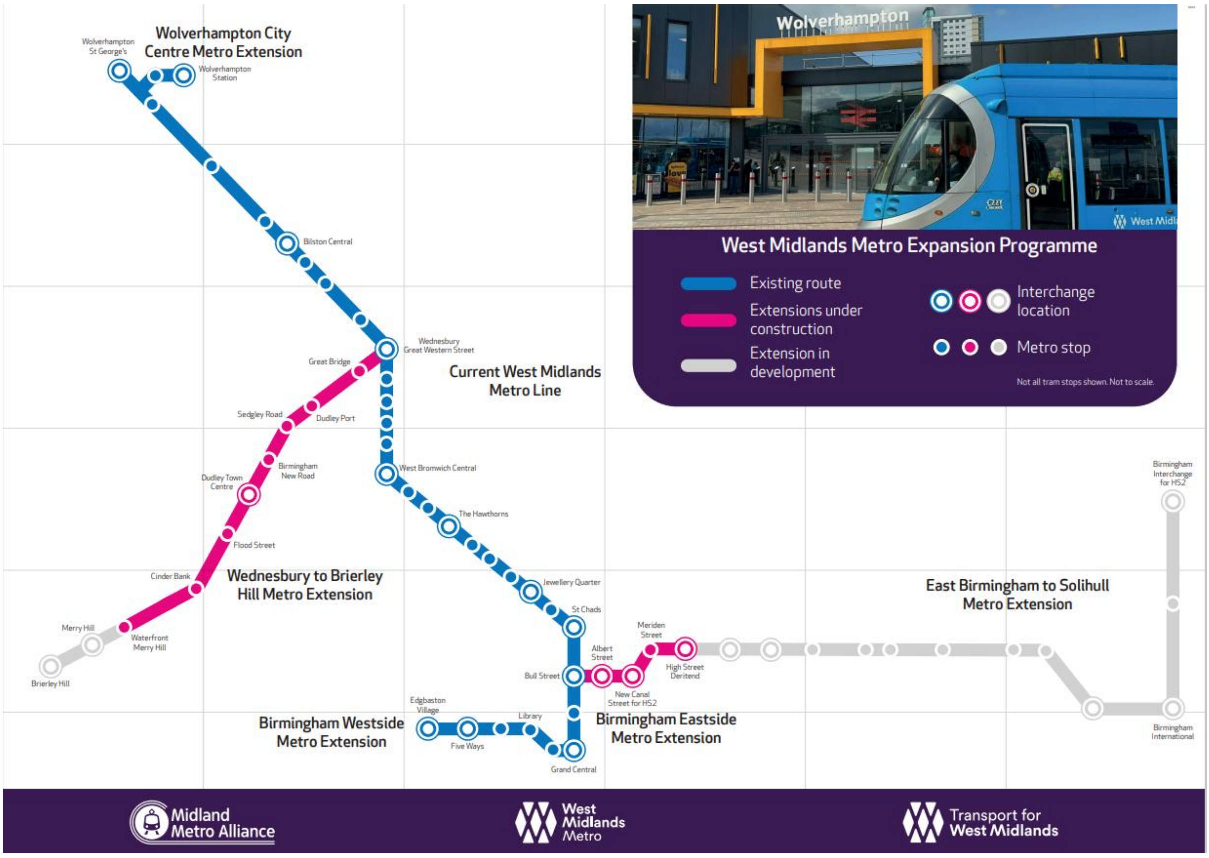

Figure 11: Metro expansion map (Source: Metro Alliance 2023)

5.2.3 PROPOSED AI / DATA SCIENCE APPROACH

Metro demand prediction under expansion scenarios is a difficult task as there is the absence of historical demand data for newly built stations and the relationship between urban context and station ridership. Additionally, the evolving network structure and scarcity of new or updated stations further complicate the problem, which renders deep learning models designed for short term prediction unsuitable.

To address these challenges, this study proposes the development of a graph-based deep learning framework, drawing on the Metro-MGAT (Multi-Graph Attention Network) model introduced by Ding et al. (2024). This model captures spatial relationships among stations through a combination of geographic and semantic graphs. It allows for the integration of diverse data inputs, even in the absence of past ridership figures, by leveraging the structural attributes of the metro network and contextual urban features.

In addition, urban simulation models will be incorporated to integrate land use zoning, demographic profiles, and transit-oriented development indicators. These will support the extraction of station-level spatiotemporal features, enabling the model to infer latent demand patterns for stations not yet in operation.

5.2.3.1 DATA REQUIREMENTS

The following data sets will be required in order to accurately predict demand for the expansion, organised into key features

Spatial features

Network structure features: station centrality, number of connected stations, number of connected metro lines, transfer station status, network layer

Built environment features: population density in Birmingham, land use mix, proximity to Point of Interests (POI) e.g. schools, malls, government buildings, historical land use change.

Temporal features

Planned station opening timeline: expected commissioning date, construction phases;

Urban growth indicators over time: population growth rate, commercial development trends, historical land use change;

Seasonal variation data: expected fluctuations in demand by time of the year e.g. tourism, season, holidays.

5.2.3.2 DATA SOURCES

Planned metro expansion map: West Midlands metro, Transport for West Midlands, Midland Metro alliance.

Urban demographic and land use data: Office of National Statistics.

Existing ridership and station data: operational metro lines for model training for model training and calibration.

The proposed model is expected to provide accurate demand forecasts of station level demand at yet to be operated metro stations in West Midland metro which will inform service planning, guide infrastructure design, support long term investments and reduce the risks of over -or -under provisioning services.

5.3 TIMETABLE CREATION USING GTFS FEEDS

5.3.1 OVERVIEW

GTFS has become the standard for the providing information to passengers about transport networks. As well as, enabling public transport organisations to publish their transit data in a standardised format that a plethora of software programs can utilise. Consequently, the implementation of GTFS data in timetabling has an abundance of advantages for both operators and passengers respectively. This section will illustrate some of the key advantages of timetable creation using GTFS data, unlike the literature review, this section aims to illustrate the usefulness of GTFS in timetable creation, as well as providing some studies illustrating the specific areas to supplement the research. The key areas discussed within this paper are:

- Standardisation.
- Real-Time Information.
- Strategic Planning & Modelling.

5.3.2 STANDARDISATION

Undoubtedly, the utilisation of GTFS feeds by operators allows timetables to be released to both passengers and transit agencies through an open standard format. The main structure of GTFS data consists of 7 files: agency.txt, routes.txt, trips.txt, stops.txt, stop_times.txt, calendar.txt and calendar_dates.txt. Consequently, the files illustrated contain all relevant information relating to the operations of a passenger service, including routes, stops, timetables and calendars. In addition to these 7 files, additional files can be added to the base 7 to provide additional information, such as ticketing, translations and connection information. “Over 10,000 agencies in 100+ countries use GTFS, ensuring consistent data for multi-agency trips and simplifying travel across regions.” (GTFS 2025) Consequently, software systems, such as journey planning applications, can extract the data and can present timetables and plan journeys, without the need for complex tools and extensive user knowledge of GTFS data.

Furthermore, the output from GTFS data can be easily integrated into a plethora of applications, including internal systems for operators and public journey planners such as Google Maps. Consequently, a timetable can be integrated into journey planners and websites as well as, passenger information systems on trains and stations. Regardless of which source a passenger use to choose where to find real-time service information, the standardised use of GTFS means that this guarantees that they are receiving accurate and up-to-date information, as well as highlighting diversions and delays were applicable.

The standard format is valuable as for regions with multiple operators, transport agencies can coordinate and present information from multiple operators on one platform with ease. In addition to assisting internal operations, by leveraging GTFS standardisation, this also guarantees that passengers, outside developers, and similar regional operators receive consistent, high-quality scheduling information. Furthermore, with GTFS being the industry standard, organisations can easily publish and edit data, without the need for significant investment, in both time and software. Importantly, an important aspect of GTFS data, is when intertwined with GTFS-RT (Real-Time) feeds, real-time service updates can be provided to passengers allowing them to decide how to complete their journeys based on actual service performance, including cancellations, delays, and emergencies. Therefore, by using GTFS to create timetables directly results in enhanced customer satisfaction, with updated information being readily available for passengers.

An interesting study is presented by Devunuri and Lehe (2024), in this study, a framework that answers natural language queries regarding GTFS data by utilising Large Language Models (LLMs). The framework's open-source code is utilised in the chatbot "TransitGPT", functioning by directing LLMs to generate Python code that finds and modifies GTFS data regarding the query. The AI application can complete a plethora of activities such as, calculations, data retrievals and interactive visualisations, without the need for the user to be proficient in programming and GTFS data. Interestingly, there is no fine-tuning or access to GTFS feeds or the LLMs that generate the code; they are directly entirely by prompts. Therefore, to illustrate the adaptability and effectiveness of TransitGPT, it is evaluated across 100 tasks, utilising GPT-4o and Claude-3.5-Sonnet LLMs. Overall, the study demonstrates that the application can perform a plethora of GTFS retrieval tasks with solely text instructions, illustrating the future of GTFS applications and artificial intelligence.

5.3.3 REAL-TIME INFORMATION

As referred to earlier, a significant advantage of creating timetables with GTFS feeds is the ability to seamlessly integrate data with GTFS-RT (Real-Time), consequently providing performance monitoring for operators as well as live updates for passengers. There are two aspects to GTFS feeds: Static/Schedule and Real-Time. "GTFS Schedule contains information about routes, schedules, fares, and geographic transit details among many other features, and it is presented in simple text files" whereas "GTFS Realtime contains trip updates, vehicle positions, and service alerts, using the Protocol Buffers format." (GTFS 2025)

Consequently, operators and agencies can align scheduled services with real-time services, therefore, providing live timetables and service updates for passengers. Furthermore, this also allows for performance analysis, pinpointing disruption locations and the estimation of potential delays. Meanwhile, in real-time services can be modified dynamically to reduce disruption, by short-turning trains for example. With enhanced service information. Furthermore, real-time integration assists passenger information systems as well as journey planning apps, alerting passengers to precise wait times and potential disruption, in accordance with the original timetable. Therefore, by combining GTFS-Schedule and GTFS-Real-Time, a static timetable becomes a dynamic and adaptable system, that passengers can trust and rely upon.

An example of the implementation of GTFS data is presented by Furukawa et. al. (2023), the study illustrates that the dissemination of GTFS data amongst bus operators is progressing in Japan to achieve standardisation and the digitalisation of service data. Interestingly, whilst this data is publicly available, service operators were seemingly under-utilising it. Consequently, real-time information is not provided and the timings between intermediate stops remain constant throughout the day, as a result, buses are usually late, with unreliable information provided to passengers. Therefore, to enhance the reliability of bus timetables and to reduce the workload for operators to modifying timetables, the study proposes a method for improving timetables utilising GTFS Real-Time data to increase reliability as much as possible without causing early departures. The selected operator within the study is the Yokohama Municipal Bus, operating in Yokohama, Japan. The operator runs over 10,000 vehicles daily on approximately 600 routes. Therefore, a significant number of bus stops are expected to have persistent delays, consequently, significant work is required to update the schedule. The study introduced a framework for leveraging GTFS data to create a timetable that represents the operating performance of all routes of the specified operator. Interestingly, on some routes, the method demonstrated a considerable reduction in the number of delayed buses. In greater detail, the method selects the earliest time that satisfies either the most frequent departure time at each stop or the time represented by the ratio of buses that allow for acceptable time changes, (Allowable Waiting Occurrence Rate - AWOR) as the new departure time. For example, the average delay time was lowered by a maximum of around 7 minutes when AWOR was set at 10% as opposed to before the enhancement. Additionally, it was noted that even with AWOR set at 0%, a reduction in delayed buses was identified, consequently, illustrating that some buses were not running on time on the existing timetable. This approach is thought to be a successful way to update timetables, particularly for bus routes in cities with significant passenger and traffic volumes. On the other hand, it is thought that a better schedule can be produced by considering the availability of bus stands and other various elements that provide enhanced time adjustments. Whilst this report focuses on buses, key lessons can be learned for metro operation at high frequencies, with service bunching, high passenger volumes and the consideration of various factors.

5.3.4 STRATEGIC PLANNING & MODELLING

Another benefit of creating timetables using GTFS feeds is the ability to strategically plan and optimise services. Timetable data can be systematically aligned with other datasets such as passenger usage figures, vehicle speed profiles and former timetables. Consequently, operators can form models and simulations to test potential new timetables, across various locations, time periods, routes and the resilience of the network and statistically analysing the results. Moreover, delays to services can be analysed, comparing GTFS-Schedule times, to the GTFS-Real-Time times, therefore, providing solutions as to where to modify timetables as to where the delays occur, for example, increasing running time. Overall, by modelling and pinpointing where delays occur, operators can create more reliable and attainable timetables, increasing service performance and decreasing service disruption, therefore, improving passenger experience and reliability. Furthermore, operators can plan and reduce the operational risks associated with pre-planned disruption, such as, engineering works, whereby services are modified, by using GTFS data and modelling the proposed timetable, risks can be reduced and potential problems identified.

Furthermore, another study of interest is from Chapleau and Bisaillon (2013) highlighting the benefits of GTFS data and how it can facilitate the ability to create accurate and comprehensive models of transport networks is made possible by the development of transportation modelling technologies and the availability of very large datasets. The study presents a methodology for constructing a model of high spatiotemporal resolution that may offer fresh perspectives into the operational elements of a public transport network and the usage patterns of its passengers. As part of the study, the case study utilised is the four-line, 68-station Montreal subway system. A weekday with 883,599 person-trips is constructed using seven days of entry-only smart card validation data. Due to the fare validation only indicating the entry station, trip chain logic must be employed for determining the exit station of each passenger. An algorithm is used to carry out the derivation and assessing the level of certainty. Individual vehicle and human movements can be explicitly represented in this simulation network. Consequently, there are two separate approaches to simulate the derived person-trips, firstly, the TRANSIMS 4 platform and an SQL-based assignment algorithm. Across both approaches, the outcomes of the schedule-based simulation enable the creation of dynamic load profiles of platforms and trains, therefore, the approaches presented in the study have potential to benefit other operators and agencies in both strategic and operational planning. To illustrate the outcomes of the study, the methodologies described within the paper allow for the incorporation of large data sets into a disaggregated public transport network modelling framework with high spatiotemporal precision. A significant quantity of schedule data is used to depict the dynamic characteristics of public transportation services. Meanwhile, smart card transaction data obtained through the entry only system is employed to create a non-synthetic population of travelling agents. The data can present an opportunity to enhance our comprehension of travel behaviour inside a system. A high-resolution representation of a significant transit system can be obtained by a completely disaggregate dynamic approach to network modelling, which employs either direct assignment or agent-based microsimulation techniques. For example, the modelling can estimate the individual demand for each of 1500 cars running at 30,000 different stop times, whereas a conventional approach to simulating the Montreal subway network would result in load profiles for eight directional lines and 68 stations. Consequently, this approach to network modelling can facilitate future studies into significant factors surrounding metro operation. In addition to allowing for the accurate calculation of vehicle, station, and platform occupancy at any given time, the system has potential to be employed to construct evacuation and emergency response plans, to allow operators to have strategies and contingency plans in greater detail. Therefore, the benefits of incorporating GTFS data into modelling has plenty of strategic advantages for both operators and agencies in timetable and strategic planning.

5.3.5 SUMMARY

To conclude, this section illustrates that by creating timetables using GTFS feeds, the advantages both for operators and passengers are clear. It is now clear how crucial data-driven strategies are becoming in transit planning. The benefits and versatility of GTFS data is clear, a standardised, easily modifiable and practical approach to timetabling can be facilitated by the utilisation of both GTFS-Schedule and GTFS-RT. Operators and agencies can leverage GTFS data to provide up-to-date, reliable and dynamic scheduling for both passengers and staff respectively. For long-term service planning, multimodal coordination, and real-time updates, GTFS is a powerful tool. An example of this has been utilised in New South Wales, Australia. Analysing General Transit Feed Specification (GTFS) and GTFS-Realtime data, the research intended to assess the efficiency of bus services in Greater Sydney. In addition to measuring bus infrastructure design features at a detailed spatial and temporal resolution, the study sought to assess stop-to-stop bus performance, including journey time and reliability metrics. The study aimed to highlight inefficient road designs and suggest fixes by comparing performance data with infrastructure features like bus lanes and stop locations. Consequently, the findings are intended to improve service dependability, guide infrastructure planning, and facilitate the integration of autonomous buses by minimising conflicts between autonomous and human-driven vehicles and optimising priority lane designs. (iMove Australia 2022) Overall therefore, adopting reliable, GTFS-based timetable solutions is arguably essential to creating transport networks that are more user-centred, responsive, and efficient as public transport systems continue to develop.

5.4 ANOMALY DETECTION APPLIED ON METRO OPERATION

Anomaly detection is a critical aspect of various fields, including cybersecurity, finance, healthcare, and manufacturing. It involves identifying data points, events, or observations that deviate significantly from the norm. These anomalies can indicate potential issues such as fraud, network intrusions, medical conditions, or equipment failures.

Traditional anomaly detection methods often rely on statistical techniques and rule-based systems. While effective to some extent, these methods struggle with complex, high-dimensional data and dynamic environments. AI-based approaches, particularly ML and deep learning, offer significant advantages. They can learn from vast amounts of data, adapt to changing patterns, and uncover subtle anomalies that traditional methods might miss.

Despite its advantages, AI-based anomaly detection faces challenges. Ensuring data quality, handling imbalanced datasets, and interpreting complex models are ongoing issues. Additionally, the need for real-time detection and minimizing false positives remains critical. AI-assisted anomaly detection has made great progress, but still has its limits, with the following two being essential for our use case.

- Data Quality and Quantity: The effectiveness of AI models heavily depends on the quality and quantity of the training data. Insufficient, biased, or noisy data can lead to poor model performance
- Imbalanced Datasets: Anomalies are often rare compared to normal instances, leading to imbalanced datasets. This imbalance can cause models to overlook critical anomalies or produce biased results. Techniques to handle imbalanced data are essential but can be complex to implement.

Anomaly detection for image classification involves identifying images or regions within images that deviate from the norm. This technique is crucial in various fields, such as manufacturing, healthcare, and security, where detecting defects, diseases, or unusual activities is essential. We are working on identifying an exact use-case for a method that could combine multiple types of events an operator should be made aware of. This could be an unexpected object on the train tracks, an abandoned or forgotten piece of luggage in a station or train or a potential aggression event.

The idea is to employ automated image and video processing methods to draw special attention of security personnel to such events, to improve the response time to such incidents. Especially for the area on and around the train tracks additional sensors like ultrasound-based proximity sensors or solid-state LiDAR could be considered, as reliably detecting an absence of any type of obstacle is much more important for this use-case than identifying the type of obstacle. There exist multiple large-scale datasets, but as the difficulty of extracting anomalous state from video is much higher than detecting objects on images or classifying an area as clean or unclean, which also means producing a model that can solve these tasks requires larger datasets and a lot of computational power. We are currently in the process of reviewing available methods, datasets and how to access the CCTV data of the partners in the project in a way that complies with regulations.

5.4.1 UNCLEANLINESS DETECTION IN VEHICLE INTERIOR

This use-case has been chosen as a demonstrator for additional value that can be gained from automatically processing CCTV data in real-time. We collect a dataset of instances of clean and unclean metro stations and trains and do not have to train with or on data pertaining to crowds or individual people, designing an application for which the implications of the GDPR (EU REGULATION 2016/679) and AI Act are minimal, but also adds significant value to metro operators.

The goal is to detect sanitary issues as soon as possible, so they can be dealt with by personnel as soon as possible to enhance service quality, make cleaning easier and to inform personnel ahead of time on the type of issue by providing a highlighted region of an image of the issue, so appropriate equipment can be prepared ahead of time, which is especially relevant if the worker has to enter a train in a station and clean while the train keeps its regular uninterrupted schedule.

Using this method of real-time informed dispatch at strategically selected stations, the inconveniences of such issues can be minimized and the effort required by staff optimized.

5.4.2 ADVANTAGES OF USING PRETRAINED MODELS

Pretrained models have already been trained on large datasets, which means they can save significant time and computational resources compared to training a model from scratch. These models often achieve higher accuracy and robustness because they have learned from diverse and extensive datasets. This can be particularly beneficial in detecting subtle anomalies. Using pretrained models can significantly enhance the efficiency and effectiveness of anomaly detection systems.

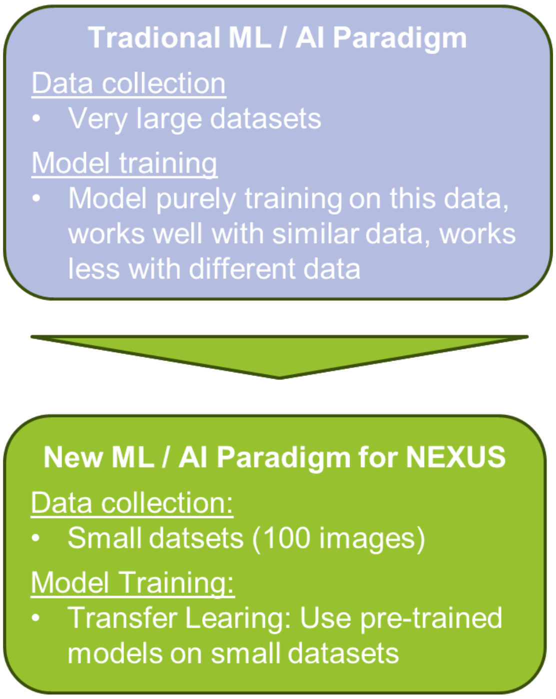

Figure 12: New ML / AI Paradigm (Source: Virtual Vehicle 2025)

There are several popular pretrained models that are widely used for various tasks, including anomaly detection. ResNet (Residual Networks) are some of the most notable ones. ResNet models, such as ResNet-50 and ResNet-101, are deep convolutional neural networks known for their ability to train very deep networks by using residual connections to prevent vanishing gradients. It is commonly used for image classification, object detection, and anomaly detection in visual data.

Anomaly detection techniques are indeed used for soiling detection, particularly in the context of solar photovoltaic panels. For this use-case we intend to use a machine learning (AI) model based on CNN. CNN are widely used for image classification due to their ability to automatically learn hierarchical features from raw image data. For anomaly detection, CNNs can be trained to recognize normal patterns, and deviations from these patterns are flagged as anomalies. We intend to fine-tune a suitable open-source model using the data we collect and other open-source datasets, then evaluate the resulting methods performance on a reserved dataset with images exclusively from metro stations or trains.

5.4.3 TRANSFER LEARNING

Pretrained models can be fine-tuned on specific datasets, allowing them to adapt to new tasks with relatively small amounts of data. This is useful in domains where labelled data is scarce. Transfer learning is a powerful technique in machine learning where a model developed for one task is reused as the starting point for a model on a second task. This approach leverages the knowledge gained from a pre-trained model to improve the performance and efficiency of a new model on a related task.

A model is first trained on a large dataset for a specific task. This dataset is usually extensive and diverse, allowing the model to learn general features and patterns. For example, a model might be pretrained on ImageNet, a large dataset of images, to recognize various objects.

The pretrained model is then adapted to a new, but related task. This involves using the pretrained model's weights and architecture as a starting point. The model is fine-tuned on a smaller, task-specific dataset. For instance, a model pretrained on ImageNet can be fine-tuned to recognize medical images.

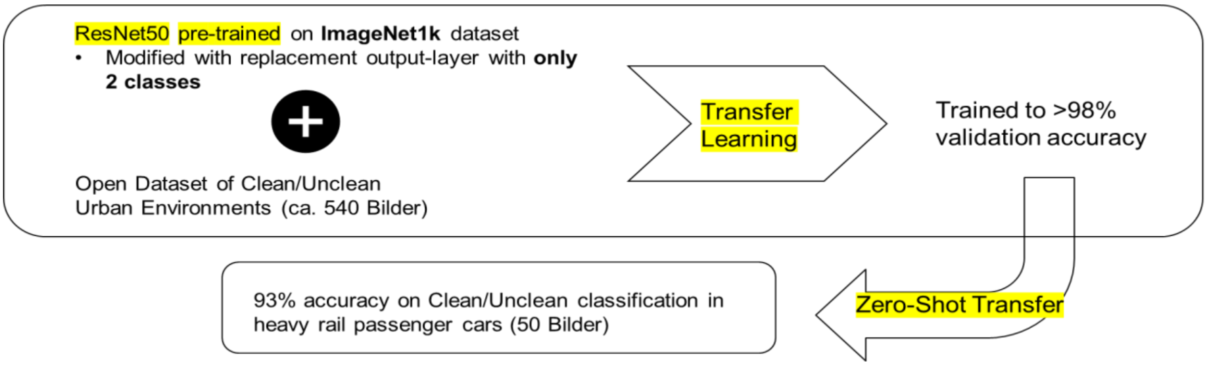

Figure 13: Image Classification with pretrained Networks (Source: Virtual Vehicle 2025)

Since the model has already learned general features, it requires less time and computational resources to train on the new task. Transfer learning often leads to better performance, especially when the new task has limited data. The pretrained model's knowledge helps in achieving higher accuracy. It mitigates the need for large amounts of labelled data for the new task. This is particularly useful in domains where data collection is expensive or time-consuming.

In this work, a pre-trained ResNet50 model was used, which was originally trained on the very large ImageNet dataset with 1000 classes. As this is a CNN that is already capable of recognising general image features, only the last layer of the model was initially adapted.

The model with this new layer was specifically trained to distinguish between two classes: clean and unclean, using softmax activation to calculate the probabilities for each class.

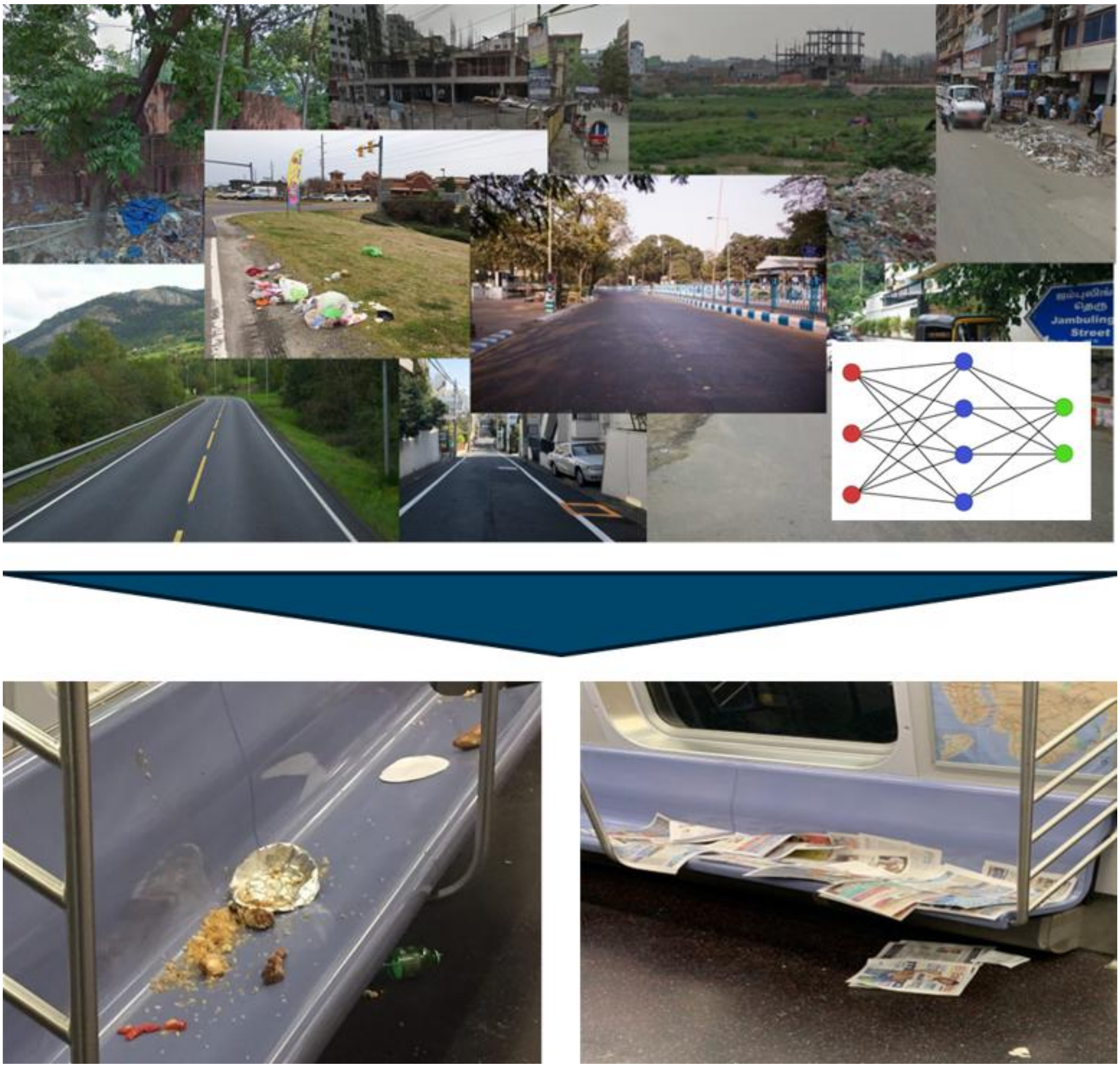

Figure 14: Transfer Function applied on Training Dataset; (Source: Hossain Y. et al. 2021 and Faizal K. 2023)

This process of re-training with parameters already learnt on another dataset is called transfer learning. The dataset on which the model was trained consisted of urban images that were classified as ‘clean’ or ‘unclean’ to represent a left and a right set of scenes that would enable cleanliness classification down the line.

However, after training on the urban data, the model was exposed to a completely new domain - the images from metro passenger cars - without any additional training or fine-tuning to this specially adapted domain. This process is known as "zero-shot domain adaptation", also known as zero-shot transfer. The model was applied directly to the images of this new, unseen domain, demonstrating the model's ability to transfer knowledge from one domain (urban images) to another, entirely new domain, without any explicit adaptation.

The preliminary results are promising, and detection is often well over 90%

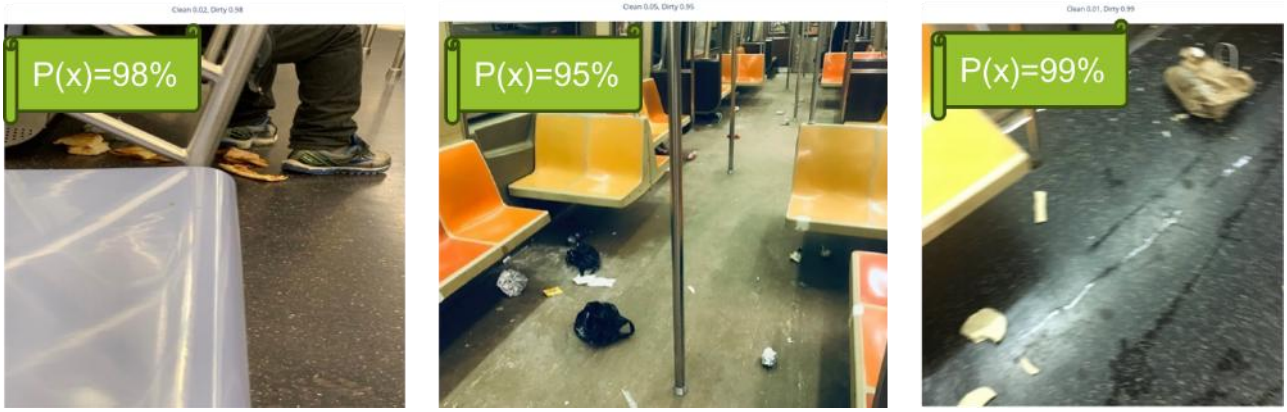

Figure 15: Image Classification - preliminary Results of Uncleanness Detection (Source: Instagram 2025)

6 GOOD PRACTICES

AI has rapidly evolved from a theoretical concept to a practical enabler of smarter, safer, and more efficient metro operations. Within urban transit systems, AI-driven passenger flow prediction—powered by deep learning, sensor data, and sophisticated analytics—has become a crucial tool to address real-time and strategic challenges, including congestion, delay management, and emergency preparedness. This chapter aims to dissect what *actually works* in practice when AI is applied to metro crowd forecasting, while also addressing the significant limitations, ethical concerns, and regulatory pressures that operators and developers face. Drawing from a wealth of academic literature and applied studies, we highlight exemplary models and frameworks, explore technical and operational hurdles, and reflect on the implications of the European **General Data Protection Regulation** (EU REGULATION 2016/679) and the forthcoming AI Act for such systems.

6.1 WHAT WORKS: BEST PRACTICES IN AI-DRIVEN CROWD FORECASTING

AI applications in metro systems are showing increasing maturity. While no universal solution exists, a few common characteristics consistently emerge among successful implementations. In the following paragraphs, some examples from the findings in Chapter 4 are reported.

6.1.1 LEVERAGING HETEROGENEOUS AND EXOGENOUS DATA

Crowd prediction accuracy greatly improves when AI systems integrate *heterogeneous data streams* (e.g., historical ridership logs, ticketing records, weather forecasts, event calendars, social media activity, and even real-time station sensors). The move from single-source models to multimodal data fusion marks one of the most important shifts in prediction quality.
The **MDN-HDNN** framework exemplifies this trend by incorporating both smart card data and social media feeds to capture irregularities like concerts, protests, or weather disruptions that traditional models often miss. The model showed improved prediction accuracy by identifying correlations between passenger spikes and increased online activity (Xue, et al. 2022).
Similarly, the **PULSE** system uses a hybrid approach that customizes its models based on station-specific attributes—such as proximity to the city centre, known peak hours, and local weather conditions—creating a tailored prediction engine for each location (Toto et al, 2016). This adaptability is key to maintaining performance across diverse urban geographies.

6.1.2 ADVANCED AI MODELS: HYBRID NEURAL NETWORKS

Deep learning architectures—especially when combined in hybrid forms—are particularly well-suited to handle the spatial-temporal complexities of metro systems. **LSTM networks** effectively capture long-term dependencies in passenger flow trends, while **GCN** model the physical connectivity of metro stations.
The **ResLSTM** model integrates GCNs (for metro topology), LSTM (for temporal trends), and ResNet (for spatial smoothing), creating a three-pronged model that processes inputs such as inflow/outflow

data, network layout, and external factors like weather (Zhang J. et al., 2021). LSTM model has been successfully tested on data from the Shenzhen metro, offering high fidelity in both routine and anomalous situations.

Another noteworthy model is **GCTN** (Graph Convolutional and Comprehensive Neural Network), which combines Transformer-based sequence modelling with convolutional and graph techniques to handle both fine-grained time-series data and structural dependencies across lines and stations (Zhan Z., et al., 2022).

6.1.3 STATION-SPECIFIC CUSTOMIZATION AND SCALABILITY

Rather than applying generic models across entire networks, several high-performing systems adopt a **decentralized or modular approach**, customizing algorithms per station or cluster of stations. This granular methodology increases accuracy, as it reflects the distinct crowding patterns caused by local demographics, land use, and service frequency.

The **funFEM-based clustering** approach, for example, groups metro stations in Seoul based on similar crowding behaviour, allowing forecasters to apply a tailored prediction method per cluster (Park Y. et al., 2022). This not only improves forecast precision but also facilitates better resource allocation (e.g., more staff or security in anticipated hotspots).

6.2 WHAT DOESN'T WORK: CURRENT LIMITATIONS AND GAPS

Despite these advances, metro AI systems are not without serious limitations. Many of which hinder broader deployment or long-term sustainability.

The **availability and quality of data** are among the most persistent bottlenecks. While large cities often have extensive datasets from smart cards and surveillance systems, smaller or underfunded metro systems may lack the granularity or completeness needed for reliable prediction. Moreover, even in data-rich environments, **real-time data streams** can suffer from latency, missing values, or misalignment between sources. For instance, an event dataset might not update fast enough for prediction systems to react, while weather APIs can sometimes offer only region-level forecasts that are too coarse for local adjustments. In cases where anomalies occur – such as spontaneous demonstrations or infrastructure failures –models trained on historical patterns often underperform, revealing their dependence on *predictable regularities*.

Many cutting-edge AI models, especially those using deep neural networks or attention mechanisms, function as black boxes. This **lack of interpretability** presents a serious challenge for metro operators who need actionable insights, not just predictions.

Understanding *why* a model predicts overcrowding at a particular station is critical, especially if operational decisions (e.g., opening alternate exits, rerouting trains, or broadcasting alerts) are to follow. Without explainability features – like saliency maps, attention visualizations, or SHAP (Shapley Additive Explanations) values – these systems are harder to trust or validate, particularly during critical events.

While the academic literature celebrates accuracy improvements, real-time inference using advanced models remains a challenge due to their **computational complexity**. Many systems require GPU-powered backends, cloud hosting, or parallel computing frameworks. This makes them difficult to adopt for cities with limited IT infrastructure or budget constraints.

Finally, models trained in one context (e.g., Beijing) often struggle to generalize to another due to differing cultural behaviours, transit layouts, and demographic profiles. This reveals the need for transfer learning techniques or domain adaptation frameworks as a still a developing area in this field.

6.3 GDPR, THE AI ACT, AND LEGAL-ETHICAL CONSIDERATIONS

As AI-based passenger flow prediction systems are increasingly integrated into metro operations, they raise pressing legal and ethical questions. Particularly regarding personal data processing, algorithmic accountability, and fairness. These issues are especially pertinent in the European context, where two cornerstone regulatory frameworks shape the boundaries of acceptable AI use: the **GDPR** and the proposed **AI Act**.
These regulations do not merely impose compliance obligations; they also offer a framework to build **trustworthy AI systems** that are transparent, human-centric, and respectful of individual rights. Below, the key intersections between predictive AI in metros and these regulations are analysed, identifying practical tensions and best practices for developers and operators.

6.3.1 DATA PRIVACY, PSEUDONYMIZATION, AND THE CHALLENGE OF 'PERSONAL DATA'

AI systems in public transport often rely on granular data such as smart card usage, mobile app logs, station-entry timestamps, and even Bluetooth or Wi-Fi signals. Although these datasets may be *de-identified* at first glance, they often contain **persistent identifiers** (e.g., card IDs, device hashes) that make it possible to trace individual movement patterns over time. Under the GDPR, such data is still considered **personal data**, unless it is irreversibly anonymized.
One critical distinction lies between:

- **Anonymized data**, which falls outside the scope of GDPR; and
- **Pseudonymized data**, which remains subject to full GDPR protection.

In practice, true anonymization is difficult to guarantee in mobility contexts, given the risk of re-identification by correlating movement patterns, location, and time. As such, AI models that train on this data must ensure privacy by:

- **Applying privacy-preserving techniques** like data aggregation, k-anonymity, or differential privacy.
- **Minimizing data collection**, i.e., collecting only what is necessary to achieve the intended predictive purpose.
- **Regularly reviewing data retention policies**, ensuring that historical passenger data is not stored indefinitely.

6.3.2 AUTOMATED DECISION-MAKING, HUMAN OVERSIGHT, AND THE RIGHT TO EXPLANATION

Under **Article 22** of the **GDPR**, individuals are afforded the right not to be subject to decisions that are based solely on automated processing, particularly when such decisions have a significant impact on them. While many AI-based crowd prediction systems in the transportation sector are used for operational planning or service optimization, there are instances where these systems can have direct consequences for passengers. For example, automated decisions such as platform closures, station redirection, or altered train schedules can significantly affect individuals' travel experiences.

When a passenger is denied access to a platform or rerouted based on the output of an AI model, critical questions arise:

- Was this decision made solely by an automated system?
- Was the decision explainable?
- Was there human oversight involved?

These considerations are particularly important in the context of transportation, where decisions directly impact the safety, convenience, and rights of passengers. In addition to the rights granted under the GDPR, the AI Act further extends its focus to high-risk AI applications, including transport-related predictive systems. The AI Act classifies certain AI systems as high-risk due to their potential to impact public safety and the well-being of individuals. As a result, these systems are subject to stricter regulatory requirements, including:

Human oversight mechanisms to ensure that decisions are not made entirely by automated systems, particularly in critical situations. Robust documentation and record-keeping of decision-making processes, enabling transparency and accountability in AI model operations. Transparency toward affected individuals regarding the rationale behind decisions, ensuring that they understand how and why specific actions are taken based on AI predictions. To comply with these standards, developers and operators of AI-based crowd prediction systems in the transportation sector must implement several key measures:

- Explainable AI (XAI) methods: Techniques like SHAP, LIME, or attention visualization layers can be integrated into the AI models to enhance interpretability. These methods allow users to understand which features most influenced a prediction, making the system more transparent and explainable.
- Override protocols and manual review processes: Particularly in high-stakes or safety-critical situations, it is crucial to have mechanisms in place that allow human operators to override AI decisions. This ensures that the decision-making process is not entirely dependent on automated systems, and human judgment can be applied when necessary.

While the technical mechanisms for oversight are crucial, it is equally important to consider the organisational and human resources implications of deploying AI systems in transport operations. The shift toward AI-assisted or AI-led decision-making could reshape job roles, require reskilling of staff, and create new responsibilities around system monitoring, compliance, and ethics. These implications extend beyond the technical domain and touch on broader workforce dynamics and public trust. The ethical, social, and human resources impacts of AI in public transport, including potential biases, deskilling, or job displacement, will be further explored in the dedicated WP11 – Ethics Requirements of this project. This WP will address the human-centric considerations needed to ensure that AI systems enhance — rather than undermine — the well-being, autonomy, and rights of both passengers and transport staff.

6.3.3 FAIRNESS, NON-DISCRIMINATION, AND URBAN EQUITY

Beyond individual privacy, AI systems in metro operations must also meet broader standards of **fairness** and **non-discrimination**. Models trained on historical data can inadvertently **perpetuate structural biases**—for instance, by allocating fewer resources to low-income neighbourhoods where ridership is lower, or by reinforcing racial, gender, or accessibility inequities.
The EU's AI Act places a strong emphasis on **data governance**, requiring developers to:

- Audit training datasets for representativeness;
- Ensure that protected attributes (like ethnicity or disability status) are not directly or indirectly leading to discriminatory outcomes;
- Evaluate the impact of prediction-based decisions on vulnerable groups.

A growing area of research within AI ethics is the development of **fairness-aware machine learning**, which introduces metrics like demographic parity, equal opportunity, and counterfactual fairness. Applying such principles to crowd prediction could ensure that metro services remain inclusive, particularly during policy decisions like where to increase train frequency or invest in infrastructure.

6.3.4 ACCOUNTABILITY, DOCUMENTATION, AND REGULATORY READINESS

Under both GDPR and the AI Act, **accountability** is not just a principle, but it is a legal requirement. Transit authorities and AI developers must demonstrate compliance through:

- **Clear documentation** of data collection practices, model design, and risk mitigation strategies;
- **Impact assessments**, such as Data Protection Impact Assessments, especially for high-risk processing;
- **Incident reporting mechanisms**, should a model fail or behave unpredictably.

Anticipating the enforcement of the AI Act, transit agencies must begin preparing for potential audits or certification schemes, which may be required for AI systems deemed high-risk. These certifications will likely focus on explainability, safety, human control, and cybersecurity.

NEXUS is properly structured to be compliant with the accountability. The figures of the Data Project Officers (DPOs) and Data Protection Controller (DPC) were identified and reported in D1.2 – DATA MANAGEMENT PLAN – 1ST RELEASE both for the project and NEXUS partners.

7 CONCLUSION AND OUTLOOK

The objective of the NEXUS project is to establish an innovative benchmark, addressing crucial challenges and guiding European metros toward transformative futures. Through optimization, analysis, energy and service efficiency, NEXUS aspires to pioneer innovative solutions in two European cities (Genoa, Italy and Sofia, Bulgaria) for the urban and metro transport of the future.

The primary goal of this document is to equip readers with key insights into future metro operations, specifically focusing on how **AI** and **data science** can be leveraged to enhance system performance. It explores relevant use cases and offers practical implementation guidelines to support the integration of these cutting-edge technologies into metro networks. This document provides a comprehensive review of the current landscape of Data Science, Machine Learning, and Artificial Intelligence applications in the context of future metro operations. It introduces and contextualizes the foundational concepts of data science, machine learning, artificial intelligence, and metro operations and explores the anticipated impact of the EU AI Act on the development and deployment of AI-related use cases within this domain.

The widespread adoption of digital technologies across industries—and particularly within metro operations—has led to the generation of vast amounts of data. When effectively analysed, this data becomes a powerful asset, enabling improved decision-making and the optimization of operational efficiency and overall system performance. This deliverable draws on extensive desktop research, reviewing a curated selection of key industry reports and publications that explore the role of AI and data science in public transport. It identifies and analyses emerging trends, current applications, and notable use cases within the sector.

Additionally, it assesses the state-of-the-art in metro operations and AI integration from the perspective of a train manufacturer, offering insights into ongoing innovation and technological progress. This analysis is further enriched by findings from two industrial workshops, which provided practical, real-world perspectives and highlighted industry needs related to AI implementation. Building on this foundation, the deliverable provides a detailed examination of four representative AI use cases in metro operations: crowding prediction, demand forecasting, timetable creation support, and anomaly detection, with a specific example focused on uncleanliness detection. These use cases, grounded in existing academic and industry literature, illustrate the potential of AI technologies to enhance operational efficiency, passenger experience, and service reliability.

The integration of **AI, IoT, and Big Data** is poised to revolutionize metro systems, transforming urban transportation into a more intelligent, efficient, and sustainable mode of mobility. These technologies will drive automation, optimize operational workflows, and enhance real-time decision-making, creating safer, more reliable, and seamlessly connected metro networks. By harnessing the power of **AI-driven analytics**, **IoT-enabled connectivity**, and **Big Data insights**, metro systems can not only improve operational efficiency but also offer enhanced safety, sustainability, and a better experience for passengers.

To move from concept to practice, these mentioned use cases are further developed through detailed implementation concepts, considering architectures, data requirements, technical challenges, and potential integration pathways. The document outlines the **data science and AI demonstrators** that are developed and delivered throughout the project, setting the stage for tangible outcomes that can be applied in real-world metro systems.

In all activities, there was close coordination and constant communication with the sister work packages, especially WP4 (Models supporting metro adaptability analysis) and WP5 (Future Train Control Systems Feasibility Study). This ensured close dovetailing of the research work and avoided any unnecessary duplication of work. The use cases mentioned are in an initial phase, mainly in the feasibility check phase, and will be further developed and continued in year 2 of the project.

As the transportation sector faces increasing demands for smarter, more adaptable infrastructure, understanding how AI and data science can drive metro systems forward is crucial. The deliverable aims to provide readers with the foundational knowledge necessary to understand the transformative potential of these technologies and their real-world applications.

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9 ANNEX

MARKET RESEARCH ON AI IN METRO BUSINESS

The tables below present the results of a market research study, which inform the content of Section 4.

Vendor	Used in Metro Operations?	Potential use in metro operations?	Category	Name of solution	Solution	Assumed use of AI
Alstom	Yes	Yes	Operational Efficiency & Maintenance	Health Hub	The goal of HealthHub is to collect data from various vehicle and infrastructure sources to provide predictive maintenance information.	Advanced Analytics: HealthHub collects and processes data from trains, signaling systems, and infrastructure using sophisticated algorithms. This helps in understanding the Real-time behaviour of these systems. Predictive Maintenance: By analysing historical and Real-time data, HealthHub can predict potential failures before they occur. This allows for timely maintenance interventions, reducing downtime and improving system reliability. Condition-Based Monitoring: The depot continuously monitors the condition of train fleets using AI-driven tools. This helps in identifying issues early and performing maintenance based on the actual condition of assets rather than on a fixed schedule. Data Integration: AI integrates data from various sources, providing a comprehensive view of asset health.
Alstom	Yes	Yes	Operational Efficiency	Alstom's digital depot	The primary goal of Alstom's Digital Depot is to enhance the efficiency, reliability, and availability of railway operations through	Condition-Based Monitoring: The depot continuously monitors the condition of train fleets using AI-driven tools. This helps in identifying issues early and performing maintenance based on the actual condition of assets rather than on a fixed schedule.

Vendor	Used in Metro Operations?	Potential use in metro operations?	Category	Name of solution	Solution	Assumed use of AI
					the integration of advanced digital technologies.	Data Integration: AI integrates data from various sources, providing a comprehensive view of asset health. Advanced Analytics: Advanced analytics are used to process this data, supporting informed maintenance decisions. Predictive Maintenance: AI helps in planning and optimizing maintenance activities, ensuring that resources are used efficiently and effectively. Energy Consumption Optimization: AI algorithms are also used to optimize energy consumption, contributing to more sustainable and cost-effective operations
Alstom	Yes	Yes	Predictive Maintenance	InfraScanner (used for Health-Hub)	The InfraScanner is a specialized tool for monitoring and assessing the condition of railway tracks to detect anomalies such as track misalignments or excessive wear.	Pattern Recognition: AI algorithms analyse data collected by InfraScanner to recognize patterns and detect anomalies such as track misalignments or excessive wear. Predictive Analytics: By processing historical and Real-time data, AI can predict potential issues before they become critical, enabling timely maintenance interventions.
Alstom	Yes	Yes	Predictive Maintenance	Train Scanner (used for Health Hub)	TrainScanner provides predictive maintenance and continuous assessment of rolling stock’s technical condition. Thanks to digital	Condition-Based Monitoring: TrainScanner continuously monitors the condition of train components such as wheels, brake pads, and pantographs. AI-driven tools help in identifying issues early and performing maintenance based on the actual condition of assets.

Vendor	Used in Metro Operations?	Potential use in metro operations?	Category	Name of solution	Solution	Assumed use of AI
					data analysis, it identifies the optimal moment for component replacement.based on 3D Scanners and Lasers. Focus: Wheels, brakepad and pantograph carbon stripes	Advanced Analytics: Advanced analytics are used to process this data, supporting informed maintenance decisions. Predictive Maintenance: AI algorithms analyse Real-time and historical data to predict potential failures before they occur. This allows for timely interventions, reducing downtime and improving reliability. Data Integration: AI integrates data from various sources, providing a comprehensive view of asset health.
Alstom	Yes	Yes	Operational Efficiency	CBTC / driverless CBTC	The goal of Alstom's CBTC (Communications-Based Train Control) range, including the Urbalis solutions, is to enhance the efficiency, capacity, and safety of urban transit systems to maximize network capacity and improve operational efficiency.	Real-time Data Processing: The AI processes Real-time data from platform sensors to optimize operations Predictive Analytics: AI algorithms predict potential maintenance needs, reducing downtime and improving reliability Traffic Management Optimization (Algorithms): AI optimizes train schedules and headways to maximize network capacity and reduce congestion Energy Efficiency Optimization (Algorithms): The system uses AI to optimize energy consumption, reducing overall operational costs

Vendor	Used in Metro Operations?	Potential use in metro operations?	Category	Name of solution	Solution	Assumed use of AI
						Collision Avoidance: AI ensures safe distances between trains, preventing collisions and enhancing passenger safety Real-time Updates for Customers: AI provides passengers with Real-time updates on train schedules and crowd levels, enhancing their travel experience.
Alstom	Yes	Yes	Operational Efficiency	Urbalis Flo (APM & Monorail Signalling)	Urbalis Flo is a sophisticated signalling solution for Automated People Movers (APM) and monorail systems. This cloud-based system leverages AI and IoT technologies to transform maintenance processes and enhance operational efficiency for GoA4 operations, real-time data collection and analysis, as well as proactive maintneance.	Real-time data processing: AI continuously monitors train positions, speeds, and headways using Real-time data from various sensors Predictive Maintenance: AI algorithms analyse operational logs to predict potential maintenance needs, reducing downtime and improving reliability Traffic Management Optimization (Algorithms): AI optimizes train schedules and headways to maximize network capacity and reduce congestion Energy Efficiency Optimization (Algorithms): AI optimizes energy consumption, reducing operational costs and environmental impact Collision Avoidance: AI ensures safe distances between trains, preventing collisions and enhancing passenger safety.

Vendor	Used in Metro Operations?	Potential use in metro operations?	Category	Name of solution	Solution	Assumed use of AI
Alstom	No	Yes	Operational Safety	Tramway & LRV signalling)	Alstom's Tramway & Light Rail Vehicle (LRV) signalling solution provides advanced assistance for operations and safety, such as automated speed and breaking of manual trains in case of danger	Machine Learning: Machine learning models can recognize patterns and suggest solutions, significantly speeding up troubleshooting. Predictive Maintenance: Analyzes operational logs to foresee potential issues and diagnose malfunctions quickly.
Alstom	Yes	Yes	Operational Efficiency & Safety	Urbalis Vision™	Urbalis Vision is a comprehensive network control system developed by Alstom for metro, suburban rail, and tram operations for advanced traffic management and energy efficiency.	Predictive Maintenance: Machine learning models analyse operational logs to foresee potential issues, diagnose malfunctions quickly, and suggest solutions to technicians. Machine Learning: Machine learning helps in identifying and managing incidents efficiently by analysing patterns and predicting potential disruptions (Smart Incident Management) Traffic Management Optimization: AI algorithms optimize train schedules and headways to maximize network capacity and reduce congestion.
Alstom	Yes	Yes	Operational Efficiency & Safety	Alstom Onvia Lock™ interlocking family	Alstom's Interlocking 4.0 solution aims to enhance rail safety, capacity, and reliability by using digital technology to control	Predictive Maintenance: AI algorithms analyse data from various sensors to predict potential failures before they occur, reducing downtime and maintenance costs. Real-time Monitoring and Control: AI systems continuously

Vendor	Used in Metro Operations?	Potential use in metro operations?	Category	Name of solution	Solution	Assumed use of AI
					signals and points over greater distances, ensuring efficient and conflict-free train movements. This modular and scalable system integrates seamlessly with advanced train control systems and urban CBTC Systems, reducing maintenance costs and improving overall network performance	monitor rail operations, providing Real-time data and insights to optimize performance and ensure safety.
Alstom	Yes	Yes	Operational Efficiency	Wayside	Wayside systems are critical components in rail and transit operations, providing essential monitoring and control functions along the track. The solutions enhance system availability, simplify installation and maintenance, and provides advanced diagnostics and predictive analytics. It integrates seamlessly with urban rail systems, offering	Automated Inspections: AI automates inspections, improving maintenance efficiency and reducing parts replacement. Data Analytics: AI is used for data acquisition and edge processing, providing insights through diagnostic and predictive analytics. This helps in better utilization of field devices and improves operational efficiency. Predictive Maintenance: AI-driven predictive diagnostics help foresee potential issues and diagnose malfunctions quickly, reducing downtime and improving overall maintenance productivity.

Vendor	Used in Metro Operations?	Potential use in metro operations?	Category	Name of solution	Solution	Assumed use of AI
					real-time performance optimization and smart incident management	
Alstom	Yes	Yes	Operational Efficiency	Flex Care	Alstom's FlexCare solutions are designed to provide comprehensive maintenance and operational services for rail systems.	Predictive Maintenance: This uses machine learning algorithms to predict potential failures and optimize maintenance schedules. These algorithms help in optimizing operations, energy consumption, and resource allocation. Real-time Monitoring and Control: AI systems continuously monitor rail operations, providing Real-time data and insights to optimize performance and ensure safety.
Alstom	Yes	Yes	Operational Efficiency	Agate	The goal of Alstom's AGATE Train Control and Information Systems is to enable the digital transformation of trains by providing advanced connectivity, control, and monitoring capabilities to ensure high-performance connectivity and seamless communication between onboard systems.	Pattern Recognition: AI algorithms analyse data from onboard systems to recognize patterns and detect anomalies, ensuring efficient monitoring and control. Real-time Monitoring and Control: AI systems continuously monitor rail operations, providing Real-time data and insights to optimize performance and ensure safety.
CAF	Yes	Yes	Operational Efficiency	LeadMind	LeadMind is a digital platform designed to	Predictive Maintenance: AI algorithms analyse data to predict potential failures and optimize maintenance

Vendor	Used in Metro Operations?	Potential use in metro operations?	Category	Name of solution	Solution	Assumed use of AI
					enhance the operation and maintenance of railway fleets through advanced data analytics and real-time monitoring.	schedules. Advanced Analytics & Machine Learning: AI-driven analytics help reduce repetitive failures and improve overall fleet performance. Real-time Monitoring and Control: AI systems continuously monitor rail operations, providing Real-time data and insights to optimize performance and ensure safety.
CAF	Yes	Yes	Predictive Maintenance	Automatic Inspection Station	Automatic Inspection Station. The station uses high-resolution 3D and 2D imaging to capture detailed images of train components such as bogies, pantographs, wheels, brakes, underframes, roofs, and car body sides. These images are automatically acquired as the train passes through the inspection station.	Predictive Maintenance: AI algorithms analyse data to predict potential failures and optimize maintenance schedules. Advanced Analytics: AI-driven analytics help reduce repetitive failures and improve overall fleet performance. Image and Video Analysis/Articifical Vision: AI is used for image and video analysis.
CAF	Yes	Yes	Operational Efficiency & Safety	Optio (Signalling-CBTC)	Optio is CAF's advanced Communication-Based Train Control (CBTC) system.	Train Operations Optimization: AI algorithms help manage Real-time rail operations, improving efficiency and reducing delays.

Vendor	Used in Metro Operations?	Potential use in metro operations?	Category	Name of solution	Solution	Assumed use of AI
					Functions: - precise train localization - real-time operations management - automatic driving capabilities - scalability and flexibility - compliance with safety standards.	Energy Management Optimization: AI-driven analytics are used to monitor and reduce energy consumption, contributing to more sustainable transport.
Hitachi	Yes	Yes	Operational Efficiency & Predictive Maintenance	HMAX (Hyper Mobility Asset Expert) Suit for train, signalling and infrastructure	All-in-one digital asset management platform that provides transport operators with AI-enhanced digital solutions to optimize trains, signaling and infrastructure management. Partnership with Nvidia: Digital solutions are powered by the NVIDIA IGX industrial-grade edge A-platform to provide edge computing.	Predictive Analytics: AI algorithms analyse historical and Real-time data to predict potential issues before they occur, enabling timely maintenance interventions and reducing downtime. Edge Computing & Real-time processing of data: The platform uses NVIDIA's IGX industrial-grade edge AI technology to process data at the edge (on trains or infrastructure) in real time. Automated Diagnostics: AI-driven tools provide automated diagnostics, helping maintenance teams quickly identify and address issues. Data Integration: AI integrates data from various sources,

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						offering a comprehensive view of asset health and supporting informed decision-making
Hitachi	Yes	Yes	Operational Efficiency & Passenger Comfort	Flow Management	Hitachi Flow Management solution monitors traffic flow through bus and rail transportation networks, helping identify bottlenecks and enabling operators to optimise their network service. In real-time, this can help operators reroute traffic in case of an issue on one part of the network, and also to predict where more vehicles may need to be deployed to meet demand.	Passenger Flow Monitoring: AI uses cameras and sensors to count the number of passengers moving through specific areas in the transport network, such as bus stops and train stations. Passenger Flow Optimization: This helps operators manage passenger flows in Real-time and predict future issues based on historical data. Machine Learning: Machine learning models analyse historical data and current trends to predict future demand and crowding levels. Algorithms such as decision trees, random forests, and neural networks can be used to make these predictions more accurate over time. Natural Language Processing (NLP): NLP is used to process and interpret data from various sources, such as social media, customer feedback, and service reports, to provide real-time updates on service availability and crowding levels. Pattern Recognition: AI algorithms analyse video data to

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						recognize patterns and detect anomalies, such as unusual behaviour or unauthorized access
Hitachi	Yes	Yes	Operational Efficiency & Safety	Video Analytics AI for Public Safety and Security	The goal of Hitachi's Video Analytics AI for Public Safety and Security solution is to enhance the safety and security of public spaces through advanced video analytics. Key Functions: - Crime Prevention and Detection: The solution uses AI to analyse video data for the prevention and detection of crime, ensuring safe public places. - Crowd Management: It detects crowding, checks if people are wearing masks, and ensures adherence to social distancing rules, especially during pandemics.	Pattern Recognition: AI algorithms analyse video data to recognize patterns and detect anomalies, such as unusual behaviour or unauthorized access. Predictive Analytics: By processing historical and Real-time data, AI can predict potential safety issues before they occur, enabling proactive interventions. Facial Recognition & Behavioural Analysis: AI-powered facial recognition technology can identify individuals in real-time, aiding in the detection of known offenders and missing persons Real-time Monitoring & Computer Vision: Technology detects crowding by analysing video feeds to count the number of people in a given area.

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Hitachi	Yes	Yes	Operational Efficiency & Maintenance	Easy Boarding' optimisation engine	Hitachi's Easy Boarding optimization engine uses data from platform sensors, real-time train occupancy, and historical disembarking information. It can integrate with existing system sensors like CCTV and infrared beacons to count passengers. This information helps determine the best waiting positions for passengers on all platforms and provides recommendations to both passengers and station staff. Real-time updates prompt passengers to adjust their boarding positions. The solution also includes a control room interface.	Real-time Data Processing: The AI processes Real-time data from platform sensors, including ICC TV and infrared beacons, to count and track passenger movements. Predictive Analytics: It uses historical data and Real-time inputs to predict passenger flow patterns and potential bottlenecks Machine Learning and Optimization Algorithms: The AI calculates the optimal waiting positions for passengers on the platform to ensure a balanced and efficient boarding process and makes dynamic adjustments by continuously updating recommendations based on Real-time changes in passenger flow and train occupancy. Natural Language Processing (NLP): NLP is used to process and interpret data from various sources, such as social media, customer feedback, and service reports, to provide real-time updates on service availability and crowding levels.
Hitachi	Yes	Yes	Customer Experience &	360Pass mobility App	360Pass uses artificial intelligence and Bluetooth sensors to connect entire	Data Collection and Integration: The App uses Bluetooth sensor to detect and track passenger movements across various transport modes. It integrates data from different

Vendor	Used in Metro Operations?	Potential use in metro operations?	Category	Name of solution	Solution	Assumed use of AI
			Operational Efficiency		public transportation system in a specific city/area and make journeys as seamless as possible while capping costs.	transport modes (buses, trains, e-vehicles) to predict passenger flows. Machine Learning: Machine learning models analyse historical data and current trends to predict future demand and crowding levels. Algorithms such as decision trees, random forests, and neural networks can be used to make these predictions more accurate over time.
Siemens	Yes	Yes	Training	SITrain	SITrain is a comprehensive learning platform that delivers training in automation technology, drive technology, digital industry software and industrial communication, serving both Siemens internal employees and external customers	Personalized Learning Paths based on Algorithms: AI algorithms analyse individual learning needs and preferences to create customized training programs. Real-time Data Processing and Feedback: AI provides immediate feedback on exercises and assessments, helping learners understand their progress and areas for improvement. Adaptive Learning: The system adjusts the difficulty and content of training materials based on the learner's performance and progress. Predictive Analytics: AI predicts future learning needs and suggests relevant courses and materials to keep learners up-to-date with industry trends.

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						Natural Language Processing (NLP): AI-powered chatbots and virtual assistants use NLP to answer learner queries and provide support in Real-time.
Siemens	Yes	Yes	Predictive Maintenance	MoComp Bogie Diagnostic Solutions (Railigent)	MoComp Boogie diagnostics Solutions measures the vibration on the boogies and transmits it to Railigent to optimize maintenance intervals and avoid downtimes	Real-time Data Collection and Processing: AI algorithms analyse Real-time data from sensors embedded in bogie components to monitor their condition and performance. Predictive Maintenance: AI predicts potential failures and maintenance needs based on historical data and current operational conditions, allowing for proactive maintenance. Fault Detection: Machine learning techniques identify faulty mechanical components, such as dampers and springs, ensuring timely intervention. Trend Analysis: AI performs long-term condition analysis to detect patterns and trends that may indicate emerging issues.
Siemens	Yes	Yes	Passenger Comfort and Operational Efficiency	Hafas Analytics	HAFAS (HaCon Timetable Information System) is a comprehensive software solution from HaCon, a subsidiary of Siemens AG, offering various functions for public transport such as	Real-time Data Processing: AI algorithms analyse real-time data from various sources to provide dynamic updates about disruptions, fleet status, and operational data. Predictive Analytics: AI predicts potential disruptions or maintenance needs based on historical data and current conditions, enabling proactive measures.

Vendor	Used in Metro Operations?	Potential use in metro operations?	Category	Name of solution	Solution	Assumed use of AI
					detailed information on timetables, including real-time data and route planning.	Anomaly Detection: Machine learning models identify unusual patterns in data that may indicate faults or inefficiencies, allowing for early intervention. Operational Optimization: AI supports the optimization of fleet operations and connection management, ensuring efficient use of resources and minimizing missed connections.
Siemens	Yes	Yes	Ticketing (dynamic pricing for operator, Comfort for Customer)	S3 Passenger	Software for reservation, inventory management, and ticketing	Dynamic Pricing: AI algorithms adjust ticket prices in Real-time based on demand, availability, and other factors to optimize revenue. Predictive Analytics: AI analyses historical data to forecast demand, helping operators manage inventory more effectively and plan for peak periods. Operational Efficiency: AI Algorithms tailor recommendations and offers to individual passengers based on their preferences and travel history. In addition, AI algorithms optimize the allocation of resources, such as train or bus schedules, to improve overall operational efficiency
Siemens	Yes	Yes	Passenger Comfort	XiXo	The goal of XiXo, offered by eos.uptrade, is to simplify	Operational efficiency Optimization: These algorithms continuously optimize the recognition of travelled routes

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					and enhance the ticketing process for public transportation. Passengers can enter the car/train/etc. and activate their ticket by a push via their smartphone. Check-in and Check-out are handled automatically and the software is afterwards looking for the cheapest tarif.	and fare calculations, ensuring accuracy and efficiency. Real-time Data Processing: AI processes Real-time data to provide up-to-date information on traffic conditions and passenger movements. Predictive Analytics: This function helps in forecasting demand and optimizing resource allocation, improving overall service efficiency. Automated Fare Calculation: AI ensures that passengers are charged the best possible fare based on their travel patterns and usage.
Siemens	Yes	Yes	Operational Efficiency & Maintenance	Railigent X - Health States	Railigent X is a comprehensive suite of applications aimed at digitally increasing the capacity of rail systems and improving operational efficiency. Railigent X Health States is an application for predictive maintenance of vehicle and infrastructure that supports metro operators with information	Real-time Monitoring: AI continuously monitors the health of rail assets, providing Real-time insights and alerts for any anomalies. Predictive Maintenance: AI algorithms collect and analyse data from various sensors to predict potential equipment failures and schedule maintenance proactively, reducing downtime and maintenance costs. Trend Analysis: AI identifies patterns and trends in operational data, enabling better planning and optimization of rail services.

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					about the conditions of components and predictive maintenance recommendations.	
Siemens	Yes	Yes	Maintenance	Easy Spares & Easy Spares Idea	Easy Spares from Siemens Mobility is a comprehensive spare part logistics solution designed for rail systems. Easy Spares ID is a function of Easy Spares that identifies components by takinga and automatically ordering the new component within 3 minutes.	Machine Learning: The system's AI continuously learns from new data to improve the accuracy and speed of part identification. - Predictive Analytics: AI analyses historical data to forecast spare part needs, optimizing inventory management. Automated Spare Part Identification: AI algorithms enable the fast and accurate identification of spare parts using image recognition technology. This allows users to identify parts by simply taking a picture. Automated Order Processing: AI streamlines the order processing workflow, ensuring quick and efficient handling of orders
Siemens	Yes	Yes	Operational Efficiency & Passenger Comfort	Industrial AI for Metro Operators - Energy Efficient Timetabling (EETT)	EETT Helps optimizing timetables and reduces energy consumption	Energy Optimization: AI optimizes driving patterns and energy consumption to reduce overall energy usage, contributing to more sustainable operations. Delay Reduction and Optimization: AI dynamically adjusts train schedules and operations based on Real-time data to minimize delays and improve punctuality.

Vendor	Used in Metro Operations?	Potential use in metro operations?	Category	Name of solution	Solution	Assumed use of AI
						Passenger Flow Management: AI helps manage passenger flow by predicting peak times and adjusting train schedules accordingly. Operational Efficiency Optimization: AI enhances overall operational efficiency by optimizing various aspects of metro operations, from scheduling to resource allocation
Siemens	Yes	Yes	Maintenance	VEMS	VEMS is a vehicle scanner that provides a suite of automated inspection equipment for rail vehicles, utilizing AI for image and video analysis and sensor and too evaluate their service availability and safety. System is designed to enhance maintenance efficiency and operational safety for rail vehicles by virtual inspections, digital twin creation, predictive maintenance, increased efficiency, scalability and flexibility. This data can	Image Recognition: AI algorithms enable the fast and accurate identification of components and anomalies by analysing images captured during the virtual examination. Digital Twin: AI is used to create virtual replicas of physical objects or systems. Thereby, real-time data from sensors and other sources is used to mirror the condition and behaviour of their physical counterparts. Predictive Maintenance: AI analyses historical and real-time data to predict potential equipment failures and schedule maintenance proactively, reducing downtime.

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					subsequently be transmitted to the Railigent X Health States Application.	
Siemens	Yes	Yes	Passenger Comfort /Security	iCCTV	Siemens' Intelligent CCTV (iCCTV) is a comprehensive video surveillance and analytics solution designed to enhance safety, security, and operational efficiency in rail systems.	Real-Time Monitoring: iCCTV provides real-time video surveillance, allowing operators to monitor passenger flow, occupancy levels, and platform activities continuously. Advanced Analytics: The system uses AI-powered analytics to detect and analyse unusual behaviour, potential security threats, and safety-related incidents. This includes features like facial recognition, anomaly detection, and behavioural analysis. Pattern Recognition: AI recognizes patterns in passenger movement and behaviour, helping to optimize train capacity and improve passenger flow management. Crowd Management: iCCTV helps manage crowding by analysing video feeds to count passengers, monitor social distancing, and ensure compliance with safety regulations.
Stadler	Yes	Yes	Operational Efficiency	Stadler Nova Pro Depot GoA4	The goal of the Stadler NOVA Pro Depot GoA4 system is to optimize shunting operations in railway and tram depots	Real-time Data Processing: AI algorithms process data from various sensors and communication systems in Real-time to ensure precise control and monitoring of shunting operations.

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					through full automation, enhancing efficiency, safety, and resource utilization	Predictive Maintenance: AI analyses data to predict potential equipment failures and maintenance needs, thereby reducing downtime and improving vehicle availability. Routing Optimization: AI optimizes the routing of vehicles within the depot to ensure efficient use of tracks and resources. Collision Avoidance: Advanced AI-driven collision warning systems use sensor data (e.g., cameras, radar, lidar) to detect obstacles and initiate automatic braking if necessary. Adaptive Learning: The system continuously learns from operational data to improve its performance and adapt to changing conditions
Stadler	Yes	Yes	Security	Stadler Nova Smartsense (Collision Warning System)	The goal of the Stadler NOVA Smartsense system is to enhance driving safety by preventing collisions through advanced object detection technology.	Real-time Data Processing: AI enables Real-time analysis of sensor data to provide immediate warnings and initiate automatic braking if necessary. Object Detection: AI algorithms process data from multiple sensors (radar, camera, and lidar) to accurately detect obstacles such as vehicles or people on the track.
Stadler	Yes	Yes	Passenger Comfort	FIS4Stadler	The goal of the FIS4Stadler system is to provide	Real-time Data Processing: AI algorithms process Real-time data to provide dynamic updates about the route, including

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					passengers with dynamic and real-time information about their journey. This system aims to enhance the travel experience by ensuring passengers are well-informed throughout their trip.	stops, delays, and connections. Predictive Analytics: AI predicts potential disruptions or delays based on historical data and current conditions, allowing for proactive communication with passengers. Adaptive Learning: The system continuously learns from operational data to improve the accuracy and relevance of the information provided.
Stadler	Yes	Yes	Passenger Comfort	Mofis	The goal of the MOFIS® Fahrgast informations system is to provide dynamic and real-time passenger information at bus and train platforms, enhancing the travel experience by keeping passengers well-informed	Real-time Data Processing: AI algorithms process Real-time data from various sources to provide dynamic updates about actual departure times and special information. Predictive Analytics: AI predicts potential disruptions or delays based on historical data and current conditions, allowing for proactive communication with passengers. Operational Optimization: AI supports operators in optimizing connections and preventing missed connections by notifying drivers about potential delays. Adaptive Learning: The system continuously learns from operational data to improve the accuracy and relevance of the information provided.

Vendor	Used in Metro Operations?	Potential use in metro operations?	Category	Name of solution	Solution	Assumed use of AI
Thales	No	Yes	Customer Experience & safety	Intelligent video analytics (DIVA)	The Thales real-time crowd management solution, known as Distributed Intelligent Video Analytics (DIVA), is designed to enhance the efficiency and safety of railway stations and on-board trains. The solution aims to improve overall passenger safety, comfort, and travel experience by reducing dwell times and preventing congestion.	Real-time Video Analytics: DIVA utilizes AI-powered video analytics to process data from existing CCTV cameras. This allows the system to measure passenger density in Real-time without the need for additional sensors. Adaptive Learning: The system continuously learns from operational data to improve the accuracy and relevance of the information provided. Data Integration: AI facilitates seamless integration of existing data from various systems, ensuring efficient import and export of timetable and operational data. Crowd Density Monitoring: The AI algorithms analyse video feeds to determine crowd density levels. The system uses a three-color code (red, yellow, green) to indicate different density levels and guide passengers to less crowded areas. Heat Maps: AI generates heat maps of stations and trains, which are used by the Operations Control Centre (OCC) to monitor passenger movements and manage crowding effectively.
Thales	No	Yes	Predictive Maintenance &	Guavus-IQ	Thales Guavus-IQ provides operators with AI-based network analytics and	Real-time Monitoring: AI algorithms continuously monitor network performance, providing operators with up-to-date information on network health and performance.

Vendor	Used in Metro Operations?	Potential use in metro operations?	Category	Name of solution	Solution	Assumed use of AI
			Operational Efficiency		operational capabilities as well as machine learning (ML) for predictive maintenance	Automatic Fault Detection: The system uses AI to automatically detect faults and anomalies in the network, helping to identify issues before they impact service quality. Predictive Maintenance: By analysing historical and Real-time data, AI predicts potential network failures and maintenance needs, allowing for proactive maintenance and reducing downtime 1.
Thales	No	Yes	Operational Efficiency	Green Speed	The goal of Thales' GreenSpeed product is to optimize train operations for energy efficiency and reduce emissions and enhance punctuality and comfort	Speed Optimization Algorithms: AI algorithms continuously analyse Real-time data to determine the optimal train speed. This helps in reducing energy consumption and emissions by minimizing unnecessary braking and acceleration. Real-time Data Processing: AI processes Real-time data from various sources, including train telemetry and environmental conditions, to provide accurate and timely recommendations to train operators