

ARTIFICIAL INTELLIGENCE IN THE ROAD SECTOR

A PIARC SPECIAL PROJECT



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The use of Artificial Intelligence (AI) is quickly growing in terms of interest, products and services across multiple sectors, including the road, transportation and mobility sectors. As part of PIARC's Special Projects programme, this report explores the growing role of AI in the road sector. It provides an in-depth analysis of the benefits, risks, and challenges of AI adoption across various stages of road infrastructure development, including planning, design, construction, inspection, operations, and maintenance. In addition to this full-length report, a separate high-impact summary report has been produced. The high-impact summary provides a concise, high-level overview of the key findings and recommendations of this study, intended for decision-makers and other stakeholders who require a more accessible synthesis of the results.

The analysis considers a wide range of socio-economic contexts, addressing the specific needs of High-Income Countries (HICs), Upper-Middle-Income Countries (UMICs), Lower-Middle-Income Countries (Lower MICs), and Low-Income Countries (LICs) and providing separate recommendations for each to ensure a comprehensive and inclusive approach¹.

Using a multi-method approach - literature reviews, surveys, interviews, and case studies - the report assesses AI utilisation and maturity and also presents an expected 'To-Be' vision for AI adoption in the road sector by 2030. The study shows that AI adoption in the road sector varies, driven by technological infrastructure, workforce capabilities, and regulatory frameworks. HICs, especially in Europe, North America, and parts of Asia, are at the forefront, benefiting from advanced infrastructure and governance. In contrast, LMICs often face significant barriers, including limited resources, skills gaps, and regulatory challenges.

The most prominent uses of AI in the road sector were found to be in the areas of (i) road safety, (ii) infrastructure inspection and (iii) traffic operations / incident management and the most commonly reported benefits related to reductions in traffic accidents, improved driver safety and cost / time saving efficiencies. The most prominent challenges were either technical in nature or related to resistance to change amongst the workforce, highlighting the importance of education and upskilling to address concerns around trust in AI technologies and fears of job replacement among staff.

This report offers detailed recommendations for road administrations and PIARC, focusing on the effective integration of AI technologies. A number of specific recommendations are provided, in Section 6, on how to maximise the likelihood of achieving various benefits, and on how to overcome the common challenges and risks associated with AI adoption. In Section 7 these recommendations are summarised, initially presenting high-level guiding principles for AI adoption, followed by roadmaps outlining the transition from 2024 to 2030. These roadmaps include key pillars which should be used to guide road administrations. The roadmaps are followed by a set of general recommendations to road administrations, along with more tailored recommendations for

¹ This report categorises countries into four income groups as recognised by the World Bank: HICs, UMICs, Lower MICs, and LICs. Additionally, the abbreviation LMICs is used throughout the report to collectively refer to all UMICs, Lower MICs, and LICs together.

countries with different levels of socio-economic development. Some of the key recommendations for road administrations and PIARC are reproduced below, and full details can be found in Sections 6 & 7.

1.1.1 Key recommendations for road administrations

- Learn from existing case studies / pilots to understand the range of problems which AI can help solve.
- Invest in pilots and trials with a view to enabling larger scale deployments.
- Establish foundational policies/procedures to ensure effective, ethical & sustainable AI deployment.
- Invest in enabling infrastructure to facilitate AI adoption.
- Invest in education and awareness to ensure that everyone is on the same journey.

1.1.2 Key recommendations for PIARC

- Promote international standards for AI.
- Support capacity-building initiatives and facilitate knowledge exchange.
- Facilitate international collaborations.
- Provide technical assistance to LMICs.
- Develop an AI working group / consider implications of AI on existing PIARC Technical Committees.

Overall, this study highlights AI's potential to significantly enhance safety, efficiency, and sustainability in the road sector. While LMICs face additional challenges due to regulatory, financial, and human capital constraints, the recommendations will support road administrations and PIARC members in overcoming these barriers and unlocking the full benefits of AI by 2030.

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1. INTRODUCTION

Section highlights	
Contextual framework	An overview of PIARC's special project mechanism and the significance of AI in addressing emerging challenges in the road sector.
Key definitions, objectives and scope	Introduction of essential definitions, the objectives guiding the exploration of AI's benefits and risks, and the specific areas of focus regarding current and future AI applications in road infrastructure.

1.1. BACKGROUND

PIARC established a Special Projects mechanism to address emerging issues beyond its regular Strategic Planning Cycle. In late 2023, member countries highlighted Artificial Intelligence (AI) in the road sector as a priority for international knowledge sharing. Following an open call in February 2024, ROD Consulting Engineers were selected to deliver the “AI in the Road Sector” project under PIARC’s guidance.

1.2. DEFINITIONS

In line with the call for proposals produced by PIARC, the following definitions apply:

AI, including Generative AI as a subset, refers to the capability of digital computers, machines, or software to perform tasks typically associated with intelligent beings. This term often describes the development of systems equipped with human-like intellectual processes, such as reasoning, discovering meaning, generalising, and learning from past experiences.

AI applied to the road sector: When applying AI to the road sector, certain programmes can augment human decisions in performing specific tasks, thereby enhancing efficiency in various activities. A key benefit of AI lies in tasks where machines can enhance human capabilities, often involving repetitive tasks across large amounts of data, such as object detection in videos. Additionally, AI is creating new opportunities for services and management that were previously impossible, such as improved traffic monitoring and enhanced predictive maintenance.

In addition to the above definitions, the authors, in agreement with POT, have introduced further distinctions. These definitions aim to differentiate between benefits that are directly attributable to the activities of National Roads Authorities (NRAs), Road Operators (ROs) and their supply chain, as opposed to benefits that have a broader societal impact. To make appropriate distinctions, benefits have been classified into three categories: “Operational Benefits to NRAs/ROs”, “Societal Benefits”, and “Mixed Benefits”. This classification helps to define the scope and impact of each type of benefit, as outlined in this report. The definitions and examples for each category are detailed below.

Operational benefits to NRAs/ ROs refer to the advantages that directly enhance the operational efficiency, performance, and effectiveness of NRAs, ROs or their direct supply chain (i.e. their contractors, consultants and service/technology providers). These benefits are primarily concerned

with improving internal processes, resource utilisation, quality, accuracy, cost-effectiveness, and decision-making capabilities within the organisation.

Example: An AI-driven predictive maintenance system delivers internal advantages, enabling NRAs to anticipate road wear and tear with greater accuracy. Predicting maintenance requirements before they become critical allows NRAs to schedule repairs proactively, thereby minimising unplanned road closures and lowering maintenance costs. As a result, resources are allocated more efficiently, and operational workflows are optimised.

Societal benefits consist of the positive impacts that AI technologies have in an external context including impacts on road users, communities, and the wider public. These benefits often translate into enhanced safety, improved user experience, reduced travel times, and reduced environmental impacts.

Example: Implementing AI-based traffic management systems that utilise real-time data to optimise traffic flow can yield significant external benefits. For instance, by adjusting traffic signals dynamically to reduce congestion, these systems can decrease travel times for commuters, lower vehicle emissions, and improve overall road safety. Such improvements enhance the user experience and contribute to a more sustainable and efficient transportation network.

Mixed benefits are those that deliver advantages to both the internal operations of NRAs/ ROs and also provide external benefits. These benefits often arise from AI technologies that improve internal processes while also directly enhancing the experience and safety of road users.

Example: AI-powered systems for scheduling and coordinating roadworks offer mixed benefits. They enhance NRAs' efficiency by automating scheduling and reducing conflicts, leading to better resource use and smoother operations. For road users, these systems provide real-time updates on roadworks, reducing delays and improving travel planning. This can lead to reduced congestion and greater certainty on journey times for road users.

1.3. OBJECTIVES

AI offers significant potential to transform the road sector, presenting opportunities to enhance road user safety and optimise infrastructure operation. It also aims to improve the efficiency of design, construction, inspection, management, and maintenance processes. This study aimed to provide PIARC members, from HICs to LICs, with comprehensive insights into the benefits, risks, and implementation challenges of AI in the road sector.

AI technologies have the potential to revolutionise various aspects of road infrastructure, leading to increased safety, reduced operational costs, and improved service delivery. However, AI adoption also presents challenges, including technological, organisational, and economic hurdles. It is crucial to understand these dynamics to effectively integrate AI into road infrastructure management.

The objectives of this study were as follows:

- To review the current state of development of AI technologies and ongoing AI advancements relevant to the road sector. This included an analysis of cutting-edge AI applications and their maturity levels.

- To identify areas where AI technologies could provide substantial benefits to PIARC members by 2030. This involved examining the potential of AI to enhance road infrastructure planning, design, construction, inspection, operations, management, maintenance, and safety.
- To highlight risks and challenges associated with different potential applications of AI in the road sector. This included an evaluation of technological, ethical, regulatory, and organisational challenges that might impact AI adoption.
- To provide specific recommendations on AI adoption in the road sector. This included developing clear guidance for all PIARC members globally on how AI adoption could be approached in their organisations, tailored to the specific needs and capacities of HICs to LICs.
- To facilitate the transfer of knowledge and successful practices from around the world. These included lessons learned from various countries on deploying and operating AI technologies and addressing implementation challenges.

Data was gathered by ROD through a comprehensive review of available literature, project-specific surveys, and interviews with key stakeholders. An analysis of various AI applications was conducted, and recommendations on how AI integration should be approached from HICs to LICs were informed by this analysis.

1.4. SCOPE

The project focused on three key areas when investigating AI in the road sector: (i) existing applications, (ii) potential near future applications (with a focus on the 2030 horizon), and (iii) the challenges and opportunities for implementing these AI solutions. An analysis of existing case studies was conducted to provide specific detailed examples of AI technologies which have been implemented / piloted in the road sector to help inform the recommendations to road administrators and PIARC members on how AI can best be integrated into different socio-economic regions.

All stages in the life cycle of road infrastructure were considered, from planning and design through to operation and maintenance. The horizontal scan included all road infrastructure assets and examined potential AI applications to the business processes of ROs and owners. The fields of expertise of the various PIARC Technical Committees were also considered. The focus was on the 2030 horizon, with recommendations targeting AI adoption within this timeframe.

Automated Vehicle (AV) applications were considered outside of the scope of this study. While some of the AI applications investigated might have secondary benefits for facilitating AVs, the study did not specifically focus on measures solely for this purpose.

Moreover, the subject of this project was not to examine in detail the financial resources required for AI implementation. Instead, the study focused on providing more global recommendations for AI adoption that would prove useful to ROs and administrators around the world.

While the horizontal scan provided a general overview of the potential opportunities, risks, and challenges associated with the introduction of AI, it was recognised that guidance might not be particularly focused on areas already well developed and most likely to provide benefits by 2030. Therefore, particular attention was given to areas, as agreed with the POT, where AI had already demonstrated significant benefits or in technologies and processes showing the greatest promise for delivering new benefits in the next 6 years (e.g., video analytics using optical character

recognition for Automated Number Plate Recognition (ANPR), which is widely used in tolling and other areas and has already provided significant benefits in the roads sector).

It is also noted that while the focus of this study was on AI-technologies, the literature review also considered certain key technologies which may not explicitly use AI, but are considered as AI-enabling technologies. For example, Augmented Reality (AR) or Virtual Reality (VR) technologies may not always explicitly include AI capabilities, but given their increasing level of adoption, and the potential for AI to be integrated, some examples are included in this report. The same can be said for certain key data collection, processing, and visualisation technologies, which may not explicitly utilise AI but serve as crucial enablers for AI-based algorithms. This inclusive perspective ensures a thorough understanding of the systems underpinning AI integration in the sector.

2. METHODOLOGY

Section highlights



Overview of the study's structured methodology for investigating AI adoption in the road sector, focusing on current applications, challenges, and regulatory frameworks.



Examination of five key research themes guiding the analysis, including the “As-Is” scenario, projected “To-Be” vision for 2030, and associated risks, opportunities, and governance needs.



Detailed description of data collection methods, including literature review and stakeholder engagement, leading to evidence-based recommendations for AI integration across diverse income contexts.

2.1. OVERARCHING METHODOLOGY

The study sought to address critical research questions concerning the adoption of AI-based technologies within the road sector, focusing on current applications as well as sector-specific challenges. Regulatory frameworks were also examined, along with opportunities and barriers encountered across countries with varying income levels. Additionally, the research examined data governance and ethical guidelines pertinent to private sector engagement while assessing workforce preparedness and the implications of AI for gender inclusion and social equity. Ultimately, the study investigated emerging capabilities and presented strategic recommendations for the effective development of AI in the road sector through 2030.

To ensure that the questions arising from these topics were thoroughly addressed, this study developed a methodology which grouped them under five key themes, as illustrated in Figure 2.1. These key themes underpinned all stages of the research, from the initial stages of information collection and analysis through to the delivery of this technical report. Adopting this approach enabled a consistent focus to be maintained on essential areas such as challenges, opportunities, risks and governance, while allowing critical questions regarding the introduction of AI in the road sector to be answered.



Figure 2.1: Key themes underpinning the research methodology.

The key research themes primarily focus on two main areas:

- The “As-Is” scenario, which examines the current and existing applications of AI within the road sector.
- The “To-Be” vision scenario for 2030, projecting the future development and integration of AI technologies. It is important to emphasise that there is no singular trajectory for all countries. The position a country may occupy by 2030 will depend on multiple factors, including its socio-economic context, existing infrastructure, level of AI adoption, and regulatory readiness. This variability highlights the need for tailored strategies that account for regional and national differences.

The remaining themes are designed to examine important topics which are essential in supporting NRAs’ understanding of how to transition from the current state to the envisioned 2030 scenarios. These themes provide guidance on the necessary changes NRAs should implement, particularly in terms of governance and relevant regulatory frameworks.

A key component of this study involved the analysis of case studies, which provided real-world examples of AI applications in road infrastructure across different regions and income levels. These case studies were crucial for identifying best practices, evaluating the effectiveness of AI technologies, and understanding the challenges faced by stakeholders. The case studies, along with the findings from the literature review and stakeholder engagement, played a significant role in shaping the “As-Is” scenario. They allowed the study to capture regional variations in AI adoption and the diverse socio-economic factors influencing AI integration. The insights from these case studies were essential for formulating the “To-Be” vision and developing actionable recommendations for HICs to LICs.

2.1.1. As-Is scenario

The first key theme of this study, i.e. the “As-Is scenario”, focuses on identifying and analysing the current state of AI applications in the road sector. A detailed understanding of the As-Is scenario was defined based on two primary activities:

- *Literature review.* A comprehensive review of academic articles, industry reports, and case studies was conducted to document existing AI applications. This review covered a broad range

of AI technologies, such as video analytics & computer vision, Machine Learning (ML) algorithms, automated traffic management systems etc. The literature review also examined existing regulations and policies relevant to AI in the road sector. This included analysing current legal frameworks and governance structures affecting AI deployment and identifying any gaps or challenges.

- *Stakeholder engagement.* Input was also gathered from several stakeholders in the roads sector (e.g. ROs, infrastructure managers, technology providers etc) through a survey and interview process. This was focused on understanding the challenges currently faced in the industry, allowing the practical applications, benefits, and limitations of current AI technologies to be documented. The stakeholder engagement also provided key information about AI technology, such as risks, barriers, challenges, many of which were not well documented in the literature.

An analysis of the findings from the As-Is scenario provided a comprehensive overview of the current utilisation of AI. It highlighted the benefits realised, as well as the challenges faced by organisations across various regions, encompassing both HICs and LMICs.

2.1.2. Challenges, opportunities & risks

Although AI technologies have become commonplace in many aspects of people's daily lives, these technological advancements do not always yield benefits and, in some cases, can introduce unwanted risks such as data security risks or cyber-physical infrastructure vulnerabilities. Even where benefits may be achievable, there may be barriers or challenges which must be overcome to ensure that these benefits are actually achieved. Human factors such as resistance to change, or lack of a skilled workforce are common challenges which may exist, alongside policy, administrative or legal barriers. Consequently, this key theme was included to ensure that the challenges, opportunities, and risks associated with AI in the road sector were investigated in sufficient detail to provide realistic and practical recommendations to PIARC members aiming to adopt AI-based technologies and move towards the envisioned To-Be scenario for 2030.

Challenges, opportunities, and risks were assessed across various technologies and processes within the road sector. This key theme also considered factors beyond direct technological applications, such as implications for gender and diversity, social equity, and the necessary measures required to mitigate adverse effects. This theme facilitated the identification of new capabilities to address existing challenges, based on a holistic assessment of potential benefits alongside associated challenges and risks, as well as the identification of emerging technologies that could provide advantages to PIARC members by 2030.

2.1.3. Preparing for change

The next key theme focused on the changes that NRAs need to implement to transition from the current “As-Is” scenario to the proposed “To-Be” vision for 2030. While advancements in software, telecommunications and technology are likely to drive these requirements, this theme examined how various elements of NRA business processes need to evolve to foster the effective and beneficial development of AI and to realise its potential benefits. Recommendations stemming from this key theme were made for countries with varying levels of economic and technological development, from HICs to LICs, taking into account typical NRA organisational structures and the workforce's knowledge and skill requirements. This consideration included NRAs and other road

management agencies as well as various contractors and suppliers who provide services on their behalf.

The theme was also aligned with existing and anticipated regulatory frameworks and governance. Additionally, the recommendations identified specific areas on which PIARC should focus during the 2024-2027 Strategic Planning Cycle.

2.1.4. Governance

The rapid development of AI has created a landscape in which technological advancements have occurred at such a pace that legislation, guidelines, and principles governing the application of AI technologies are continually lagging behind. Although legislation and governance for AI technologies are not yet well established - particularly within the road sector - there are ongoing initiatives aimed at establishing standardised regulations in this area (e.g., the EU AI Act, national AI legislation, etc.). This key research theme investigated the vision for implementing these developments. It also focused on critical governance issues that play a significant role in mitigating the various risks associated with AI implementation.

Specific attention was given to governance related to data and algorithms, particularly concerning security, control, and access, as well as the requirements for governance across different sectors, including the private sector, academic research, and government/public sector bodies. Key challenges include ensuring secure cross-border data sharing, establishing sector-wide standards for algorithmic transparency, and balancing proprietary interests with public accountability. For LMICs, fostering international collaborations and leveraging global frameworks e.g. General Data Protection Regulation (GDPR) can address gaps in data security and access. HICs must prioritise interoperable standards and cybersecurity enhancements to mitigate risks associated with cross-sector AI applications.

Governance also has a role in promoting innovation, not only by addressing risks but also by ensuring that AI technologies are adopted for public benefit. This includes encouraging broad access to data, software, and hardware, which can empower a wider range of stakeholders to contribute to AI advancements. Globally, this has been supported through national AI strategies that aim to balance innovation with inclusivity and accessibility.

Specific recommendations were formulated for PIARC members regarding the preparation of regulations and guidelines to facilitate the safe, ethical, and positive development of AI by private companies operating in the road sector. These recommendations aimed to ensure appropriate ethical practices, the protection of public interests, and the pursuit of public policy goals.

2.1.5. To-Be vision 2030

The final key theme of this study, i.e. the “To-Be” scenario, represented the vision for AI adoption in the road sector by 2030, progressing beyond the initial understanding of the “As-Is” scenario. Its primary objective was to project how AI could evolve and fundamentally transform the road sector by the year 2030. This information was primarily gathered through stakeholder engagement and, where the future plans and expectations of stakeholders were disclosed, along with the authors’ understanding of developments in the AI sector and how they are likely to permeate into the roads sector. The stakeholder engagement also provided key insights into future integration of AI technologies in the road sector along with risks and challenges which are anticipated by 2030.

Recommendations for adoption of AI technologies in the road sector emerged from the comprehensive analysis of these themes. These recommendations were tailored to address the specific needs and conditions of from HICs to LICs.

2.2. STRUCTURE OF RESEARCH METHODOLOGY

The research methodology for this study is organised around three phases, i.e. (i) information collection, (ii) data analysis & scenario development, and (iii) formulation of recommendations. Figure 2.2 presents the three phases, and the associated stages followed in this research project.

2.2.1. Literature review process

The literature review involved a systematic examination of a wide range of academic publications, industry reports, case studies, and government documents. Sources were carefully selected to ensure they provided a comprehensive overview of the current state of AI applications within the road sector. The process included an evaluation of key AI technologies across various stages of road infrastructure, including planning, construction, operations, and maintenance. Specific attention was given to regulatory frameworks, technological advancements, and the socio-economic challenges faced by countries with different income levels. The findings from this review served as a foundation for identifying best practices, technological maturity, and emerging trends in AI adoption within the sector.

2.2.2. Stakeholder engagement process

The stakeholder engagement process was crucial in capturing the perspectives of key actors in the road sector. This engagement was conducted through two main activities: surveys and interviews.

Survey process: To investigate the transformative potential of AI within the road sector, an international survey was conducted by ROD on behalf of PIARC. This high-level horizontal scan aimed to gather key information from stakeholders regarding the primary challenges faced in the road sector, as well as existing examples of AI technologies currently employed globally. The survey also sought to elicit feedback on areas where AI-based technologies were perceived as offering significant value in the near future, with a particular focus on the 2030 horizon. The results of the survey, in conjunction with the findings from the literature review and the broader stakeholder engagement process, enabled comprehensive documentation of the current state and effectiveness of AI tools in road infrastructure.

Participants were drawn from a diverse range of stakeholders, with a particular emphasis on NRAs, recognising their key role in AI integration within the road sector. This prioritisation ensures that the perspectives and challenges faced by NRAs, as primary custodians of road infrastructure, are adequately represented. In addition to NRAs, stakeholders included local road authorities, engineering and design firms, technology providers, and research institutions. The survey sought to capture their insights on both the benefits realised and the challenges encountered in implementing AI technologies.

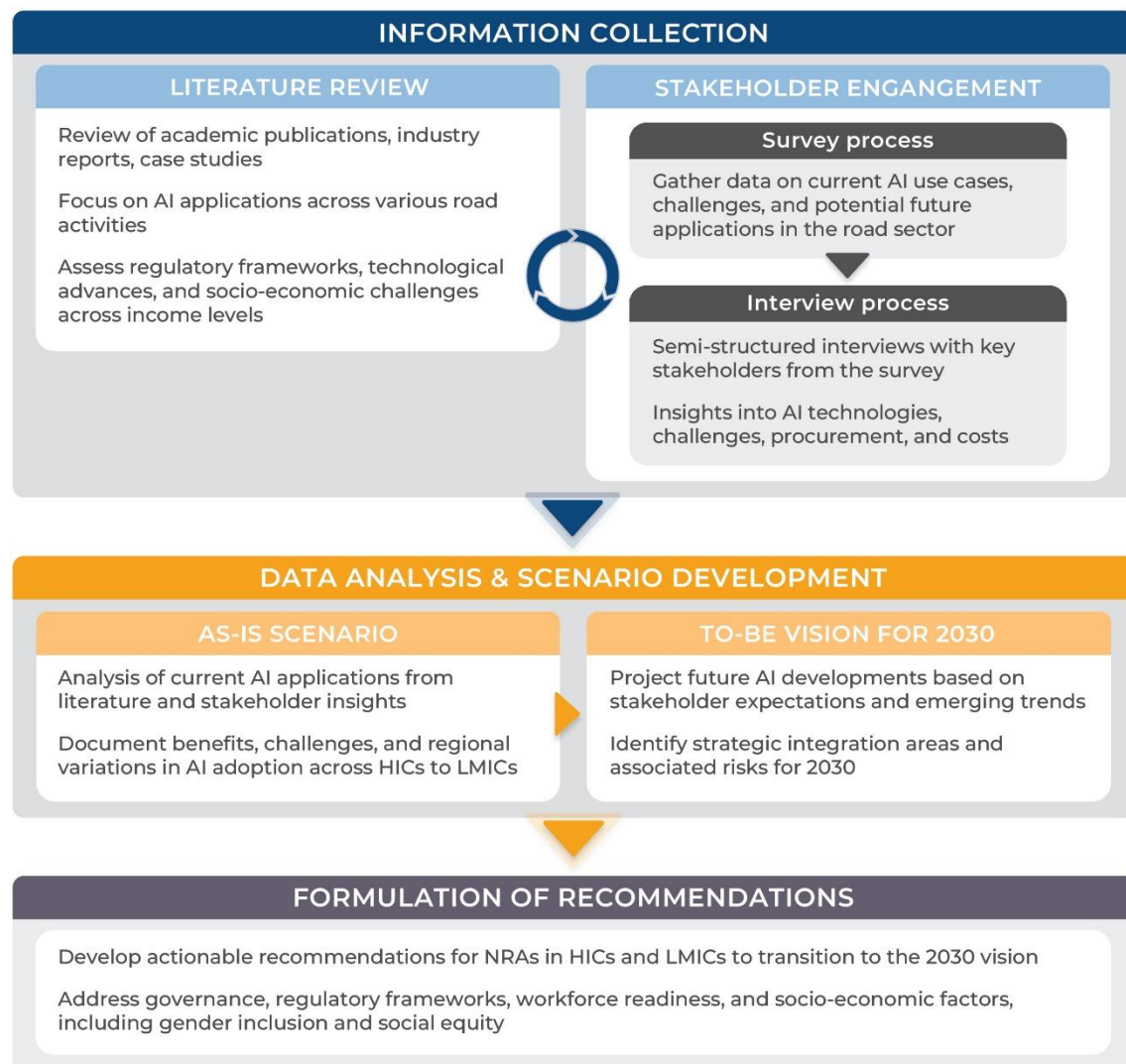


Figure 2.2: Structure of research methodology.

Additionally, it explored the state of technological infrastructure across different countries, highlighting significant variations between urban and rural areas. This information was essential for understanding the broader context of AI implementation and identifying existing gaps or disparities. The survey also played a crucial role in identifying suitable candidates for the subsequent interview process, allowing for more in-depth discussions on specific experiences with AI.

The interview methodology employed in this research was designed to extract detailed insights from professionals with direct experience in the implementation or strategic planning of AI technologies within the road sector. Following the identification of key stakeholders through an initial survey, a semi-structured interview format was utilised to facilitate flexibility and open dialogue while adhering to the specific objectives of the research and to allow specific case study examples of AI use in the road sector to be documented in detail.

Interview process: The interviews, each lasting no more than one hour, were tailored to align with three distinct sets of questions, reflecting the varied focus areas of the study. These sets of questions addressed (1) detailed case studies of AI technology pilots or implementations, (2) general perspectives and challenges of AI adoption in HICs, and (3) broader challenges and

opportunities within the road sector in LMICs. This segmentation ensured that the data gathered was contextually relevant and captured a wide spectrum of experiences and insights.

For the case study interviews, the discussions focused on the specifics of AI pilot programmes, including the technologies deployed, pre-implementation workflows, challenges encountered, procurement processes, costs incurred, and quantifiable benefits achieved. Additional emphasis was placed on barriers, risks, and lessons learned, with the aim of identifying best practices and recommendations for future AI initiatives.

In the interviews targeting HICs, the questions were designed to explore the current state of road infrastructure management, the potential role of AI in addressing operational challenges, and the barriers hindering AI adoption, such as funding, skills gaps, and regulatory limitations. Respondents were also encouraged to discuss their perceptions of the long-term impact of AI and the resources or policy changes necessary to facilitate its adoption.

For LMICs, the interviews delved into the unique challenges faced in road infrastructure management, the level of technology currently utilised, and the potential for AI to address critical issues such as data collection, maintenance, and sustainability. These interviews also examined barriers to adoption, such as resource constraints and institutional readiness, and explored strategies for overcoming these obstacles.

Across all interviews, topics related to data privacy, cyber security, job displacement, and the technical reliability of AI systems were discussed to understand the perceived risks of AI adoption. Respondents were asked to share their perspectives on existing regulatory frameworks and to suggest potential improvements to support the integration of AI in the road sector. The findings from these interviews are detailed in Section 4.2. This rigorous approach ensured that the research captured a holistic view of the opportunities and challenges associated with AI technologies in the road sector, thereby providing a robust foundation for the recommendations presented in the final report.

2.2.3. Data analysis & scenario development

The information collected from both the literature review and stakeholder engagement was synthesised to develop two key scenarios.

As-Is scenario: This scenario captures the current state of AI within the road sector, relying on findings from the literature review and stakeholder insights. It documents existing technologies, their benefits, and the challenges encountered during implementation. Notably, the analysis emphasised regional variations in AI adoption and the socio-economic factors influencing this integration, particularly between HICs and UMICs, Lower MICs & LICs.

To-Be vision for 2030: In contrast, this scenario examines how AI might be expected to transform the road sector by the year 2030. Insights gleaned from stakeholders, combined with an understanding of emerging AI trends, informed predictions regarding future developments. This vision serves as a strategic roadmap for AI integration, identifying anticipated risks, potential technological advancements, and the future needs of NRAs.

2.2.4. Formulation of recommendations

Based on the analysis of both the As-Is and To-Be scenarios, the study formulated targeted recommendations for NRAs. These recommendations address governance, regulatory frameworks,

and workforce development, providing guidance on effectively transitioning from the current state to the envisioned future (up to 2030). Special attention was given to issues of social equity, gender inclusion, and data governance, ensuring that AI technologies are deployed ethically and inclusively across HICs to LICs. This structured methodology ensures a comprehensive understanding of the challenges and opportunities presented by AI in the road sector, leading to strategic, data-driven recommendations for NRAs worldwide.

3. LITERATURE REVIEW

Section highlights



Key findings from a comprehensive review of >100 sources encompassing academic papers, industry reports, case studies, and government publications on AI application in the road sector. For full details, see Appendix B.



Outline of a categorisation framework employed for AI technologies, examining their roles across various road infrastructure activities, life cycle stages, asset types, and data utilisation.



Insights into the current and potential applications of AI across 15 key road-related activities, with an emphasis on infrastructure monitoring, road safety, and asset management.



An overview of existing legislation and governance challenges for AI in the road sector, addressing data privacy, security, and regulatory gaps.

3.1. INTRODUCTION

This section summarises the literature review process, the types of information examined and the key findings. It outlines how the literature was gathered and the methodologies used to collect and analyse the data. The review included a wide range of sources, such as academic papers, industry reports, case studies, and government publications, with a total of 148 sources reviewed to provide a comprehensive understanding of AI technology in the road sector. While the study had time constraints and may not have captured all relevant literature, the information was systematically organised and categorised to support the analysis.

This section presents key findings from the literature review. For a more comprehensive examination and full details of the literature reviewed, please refer to Appendix B.

3.2. AI TECHNOLOGY CATEGORISATION

A categorisation approach was developed to facilitate the analysis of AI technologies in the road sector, initially as part of the literature review, and then into the wider stakeholder engagement process. This approach provided a clear and structured mechanism for assessing how different technologies can be used for various activities in the road sector. The categorisation considered a number of factors, including the technology type, costs and maturity along with the relevant activities, life cycle stages and infrastructure assets for which different technologies are being used. Other important factors were also considered as part of the categorisation, such as risks, barriers or challenges for implementation, along with the associated opportunities or benefits. Full details of the categorisation approach are presented in Table A.1, in Appendix A.

3.3. AI IN THE ROAD SECTOR: CURRENT USE AND EXPECTED DEVELOPMENTS TO 2030

Based on the findings of the literature review, Figure 3.1 provides an overview of the activities in the road sector for which AI is currently being used or is under development.

The values represent the proportion of reviewed literature falling into each category and the results demonstrate that AI use is being reported across many activities. However, there is a key focus on inspection and monitoring technologies. Road safety, construction activities, operations, traffic management and infrastructure design are the next most common application areas which were identified in the literature. A total of 63% of the literature were linked to all of these activities combined, prompting increased focus on these topics as part of the later stages of this study. For example, Section 5 includes an overview of some specific case studies which are used to demonstrate the implementation of AI technologies in some of these key areas across countries with varying geographical and socio-economic contexts.

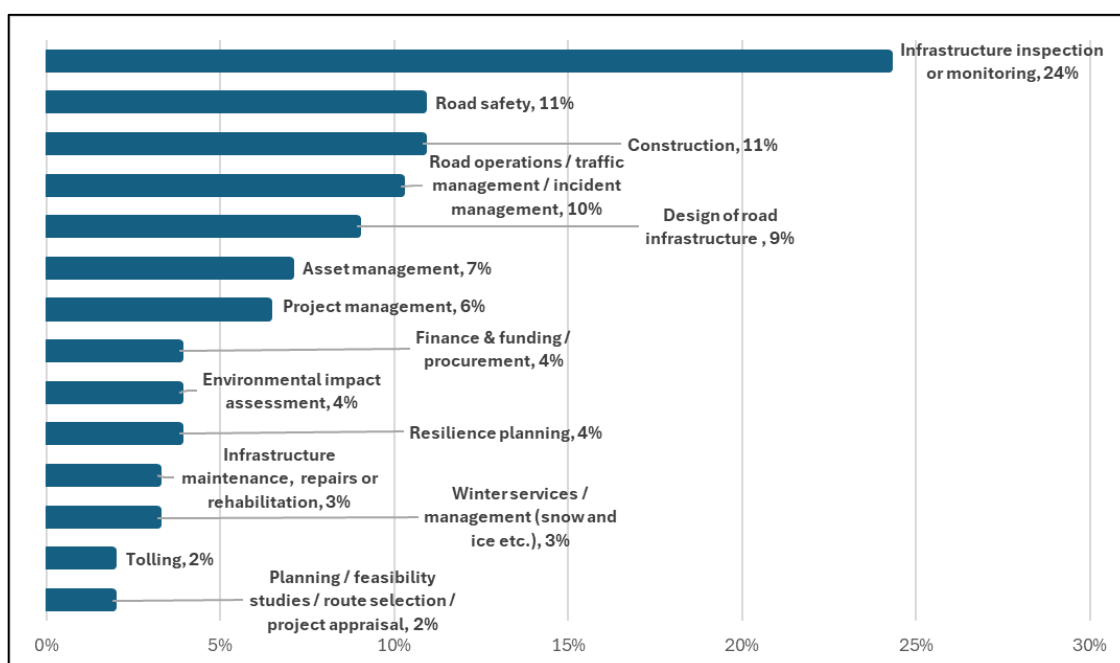


Figure 3.1: AI technologies distribution across road activities, as outlined in Table A.1 (Appendix A)

3.3.1. Current applications of AI in the road sector

The findings of the literature review indicate that the adoption of AI-based technologies in the road sector has become increasingly advanced in recent years, particularly in HICs. LMICs are exploring solutions, but the rate of adoption is noticeably slower than observed in HICs.

Table 3.1 provides a high-level overview of some of the key technologies being applied for various road sector activities. The table aims to highlight the most commonly documented technologies for each road sector activity, and the paragraphs below provide a brief commentary on some of the key observations from the literature. It should be noted that the available literature was very heavily focused on applications in HICs, and therefore the majority of the discussion in this section is focused on applications in HICs.

In HICs, AI has become an essential tool for managing traffic flows, optimising signal timings, and improving road safety. Adaptive traffic signal systems, powered by AI, adjust in real-time to traffic conditions, reducing congestion and enhancing traffic flow, especially during peak hours. These systems rely on Machine Learning (ML) algorithms that analyse traffic data from cameras, sensors, and historical traffic patterns to predict and control traffic signals effectively. Additionally, AI-based traffic management systems can dynamically allocate resources, such as adjusting lanes in response to traffic conditions, which significantly improves overall traffic efficiency.

Road safety applications of AI are extensive and varied. Although this report excludes automated vehicles from the scope, there were a number of relevant examples of AI-powered Advanced Driver Assistance Systems (ADAS), which were relevant for consideration within the scope of this study. These systems use computer vision and ML algorithms to monitor road conditions, detect obstacles, and provide drivers with warnings regarding potential hazards. In countries such as the US and several European nations, these technologies are extensively used to prevent accidents, enhance driver safety, and enable features such as autonomous braking and lane-keeping assistance. The data collected from these systems can also be leveraged by NRAs / ROs to identify portions of their networks with high-frequencies of incidents, vehicle braking events or near misses, to determine where infrastructure upgrades may be warranted to enhance overall safety.

Another prominent area of AI application in the road sector is in infrastructure inspection and maintenance. In HICs, AI is widely utilised in applications relating to predictive maintenance and the automation of asset condition inspections. Computer vision and drone-based systems, including Unmanned Aerial Vehicles (UAVs), are used to monitor road assets such as bridges, tunnels, and pavements. These systems detect defects, cracks, and wear on infrastructure components, reducing the reliance on manual inspections and enabling more frequent and detailed assessments.

For example, computer vision systems provide the ability to analyse images captured by drones or vehicle-mounted cameras to identify structural issues such as cracks in bridges or potholes/defects on pavement surfaces or other asset-related condition information (e.g. location/condition of signs, road markings etc.). AI algorithms are also used in the forecasting of future maintenance needs, allowing road authorities to leverage large quantities of data to model deterioration trends into the future and prioritise repairs based on the severity of defects.

Aside from the ability to collect much more granular asset condition data, at more regular intervals, asset management processes also directly benefit from AI technologies through the adoption of algorithms to optimise the management of road networks and maintenance schedules. AI-driven asset management systems collect and analyse data from a variety of sources, such as sensors, satellite imagery, and traffic reports, to provide insights into the condition of roads and other infrastructure. The data is processed by machine learning models to predict when certain assets may require maintenance or replacement. In some HICs, these systems have become integral to road administration strategies, enabling proactive management of road networks. AI helps to

determine which assets are at the greatest risk of failure, enabling road authorities to focus on critical areas. Furthermore, AI applications in automated scheduling ensure that road repairs and upgrades are carried out during off-peak hours, reducing disruptions to traffic and improving overall network efficiency.

AI is also being applied in the road sector to enhance environmental sustainability. Climate forecasting and environmental impact assessments are important aspects in the design and ongoing assessment and maintenance practices of road infrastructure. AI technologies, particularly remote sensing and data analytics, can play a role in this area. AI models analyse large datasets gathered from various sources, such as satellite imagery and ground sensors, to predict the environmental impact of road construction or to assess the vulnerability of road networks to climate change. In HICs, AI is helping to optimise routes for the construction of new roads, ensuring that they are resilient to extreme weather events and aligned with sustainability goals. AI-based systems for monitoring air quality and emission levels along major roadways have also been observed in the literature. One example of the benefits of such systems is in the real-time adjustment of traffic flows (e.g. using variable speed limit controls) to reduce pollution in urban areas.

ANPR systems, powered by AI, are increasingly used for toll collection and traffic law enforcement. These systems identify vehicle registration numbers in real time, allowing for efficient tolling and monitoring of road usage. AI models process the data generated by ANPR systems to analyse traffic patterns and ensure optimal toll rates, improving revenue collection and reducing congestion at toll points. In countries such as the UK, Germany, and the US, ANPR systems are already deployed extensively on highways to improve traffic efficiency and enforce regulations without manual intervention. This represents an example of AI technology which is already widely in use globally.

Other growing areas for the use of AI are in the design stage, where various ML algorithms have been proposed to automate the design process and to optimise designs to improve overall efficiency of material usage, and to minimise the carbon costs of designs. Many commercial software systems are already incorporating AI-based algorithms into their design packages. In addition, the literature review also revealed a number of examples of AI technologies being used on-site during the construction stage. Construction-related applications range from the use of automated robots to carry out site inspections and AR for visualisation of designs on site, to camera-based systems for automated enforcement of health and safety rules (e.g. warning alerts for individuals entering exclusion zones, automated detection of individuals not wearing required PPE etc.). There are also a number of documented examples of AI-based software systems for project management and scheduling/coordination of construction-stage activities.

While AI applications in LMICs are still developing, the adoption of AI in traffic monitoring and incident detection is growing, albeit in more limited or pilot stages. In countries such as India, Peru, and Kenya, AI-powered traffic management systems are being trialled to reduce congestion and improve traffic safety. AI is also being used for asset management in LMICs, where road conditions are often poor. Satellite imagery and drones are used to detect road damage and monitor infrastructure, providing authorities with a more efficient way to assess and manage road conditions. However, in LMICs, the full implementation of these technologies is constrained by financial and infrastructure limitations, and most AI applications remain experimental or are deployed in urban centres where digital infrastructure is more developed.

Table 3.1: Key AI technologies for each road activity.

Road activity	Key AI technologies documented in the literature		
Planning, feasibility, route selection, appraisal	AI algorithms for data analysis and prediction	AI-driven image processing and 3D modelling	
Resilience planning	AI for climate forecasting	Remote sensing and imaging tech	
Environmental impact assessment	AI algorithms for environmental risk analysis	Digital screening tools for evaluation	Remote sensing for environmental monitoring
Road infrastructure design	AI algorithms for road layout optimisation	AR and MR for 3D visualisation	AI generative design algorithms
Construction	DT for real-time monitoring and decisions	AR with ML for site visualisation and precision	Predictive analytics for construction management
Project management	Predictive algorithms for project planning and scheduling	AI-driven resource allocation and optimisation	AI project management tools for decision-making and efficiency
Road operations, traffic, and incident management	Adaptive traffic signal systems	AI traffic management and incident detection systems	ML for traffic prediction
Tolling	AI-driven ANPR Systems	ML for toll revenue forecasting	
Winter services and management	Autonomous snowploughs with ML and sensors	ML for slippery road detection	AI predictive algorithms for resource management
Road safety	ADAS for vehicle safety	AI-powered monitoring for driver behaviour and violations	AI road attribute classification for risk assessment
Asset management	AI mobile sensing for real-time road condition monitoring	ML for predicting road conditions using satellite imagery	
Infrastructure inspection, monitoring, maintenance and repairs	UAVs for road assets Inspections	Computer vision and ML for pothole detection and mapping	AI-based air quality and emission monitoring systems
Policy development	Data-driven insights for tailored road safety policies	AI models for traffic analysis and accident prediction	
Finance, funding, and procurement	AI cost estimation tools for budgeting and forecasting		

Abbreviations

ADAS = Advanced Driver Assistance Systems, ANPR = Automated Number Plate Recognition, AR = Augmented Reality, DT = Digital Twin, ML = Machine Learning, MR = Mixed Reality, UAV = Unmanned Aerial Vehicle.

3.3.2. Challenges and barriers to AI implementation

The literature review has highlighted a number of key challenges and barriers in relation to AI implementation in the road sector, however it is noted that the published literature tends to focus on the benefits and positive impacts of AI, and as such, the key challenges and barriers identified through the surveys and interviews are likely to be a better reflection of the practical reality.

A prominent challenge identified in the literature for HICs is the issue of data quality and reliability. Despite the presence of advanced technological infrastructure and more readily available financial resources, this still represents a significant barrier to AI adoption for many applications. AI systems depend heavily on accurate, consistent data, yet even in developed countries, road management systems often struggle with data gaps, inconsistencies, and inaccuracies. These issues can undermine the effectiveness of AI applications in areas such as traffic management and predictive maintenance and highlight the continued importance of human-based expertise and knowledge to understand and interpret the outputs from AI-based systems.

For LMICs, the challenges are more related to financial constraints and a lack of technological infrastructure. The initial costs associated with implementing AI technologies, including data collection, system integration, and staff training, can be prohibitively high. Data availability is another critical issue; many LMICs struggle with incomplete or unreliable data, which undermines the effectiveness of AI applications in predictive maintenance, traffic management, and infrastructure monitoring.

3.3.3. Predictions for 2030 based on the literature

Based on the extensive level of documented examples of AI, AI is expected to have a major impact on the road sector by 2030, with significant advances across a wide range of applications. While the trajectory of AI adoption will undoubtedly differ between HICs and LMICs, the growing trend towards automation, data-driven decision-making, and enhanced sustainability will shape the future of road infrastructure management and operation globally.

In HICs, AI is anticipated to become an integral part of urban mobility systems, expanding the capabilities of existing technologies such as adaptive traffic signal systems and intelligent transport networks. AI-driven traffic management systems will be increasingly used to optimise traffic flow, adjust signal timings, and manage congestion in real-time. These systems will rely on data from sensors, cameras, and machine learning algorithms to predict traffic patterns and adjust infrastructure settings accordingly, ultimately reducing congestion, improving road safety, and enhancing operational efficiency.

In the realm of road safety, AI applications are expected to further evolve. ADAS, such as AI-enabled collision avoidance and lane-keeping assistance, will become more widespread, reducing the likelihood of accidents caused by human error. Additionally, AI will play a crucial role in incident detection systems, allowing authorities to identify and respond to accidents and hazards more quickly. Real-time monitoring systems, using video analytics and ML to detect dangerous driving behaviours or traffic violations, will enhance road safety and facilitate timely interventions.

By 2030, AI will likely revolutionise infrastructure management across both HICs and LMICs. In developed regions, the widespread adoption of predictive maintenance and digital twins (virtual models of physical assets) will allow road authorities to optimise their resource allocation and reduce infrastructure downtime. AI-driven systems will predict the wear and tear of roads, bridges,

and tunnels, enabling proactive repairs before significant damage occurs, rather than relying on reactive maintenance. This shift will not only reduce operational costs but will also improve the longevity and safety of critical infrastructure.

In LMICs, while the implementation of advanced technologies may face more barriers, satellite imagery and drone-based inspections are expected to expand rapidly, offering cost-effective ways to monitor road conditions, particularly in remote areas. By 2030, these tools, combined with AI-powered analytics, will allow governments and local authorities in these regions to better track infrastructure needs, making it easier to prioritise repairs and improve road safety.

AI will play a crucial role in enhancing the sustainability of road networks by 2030. In HICs, AI will support the green transition by optimising traffic flow, reducing emissions, and improving fuel efficiency. AI-driven traffic management systems will be able to assess and minimise congestion, decreasing fuel consumption and emissions from vehicles. Additionally, AI will contribute to climate resilience planning, where predictive models can assess the impact of extreme weather events on roads and suggest timely interventions. The use of AI in environmental monitoring will allow for real-time tracking of air quality and pollutant levels, enabling better decision-making for urban planning and road design.

For LMICs, the role of AI in climate-resilient infrastructure will be crucial. In these regions, AI will support climate impact assessments, enabling authorities to build more resilient road networks that can withstand the impacts of climate change, such as flooding or extreme heat. The use of ML algorithms to predict environmental risks will allow LMICs to take pre-emptive action, reducing the damage to infrastructure and preventing costly repairs.

3.4. LEGISLATION AND GOVERNANCE

This section highlights key regulatory developments, challenges, and the evolution of frameworks managing AI integration, as identified in the literature review. As AI adoption accelerates in road infrastructure, the regulatory landscape struggles to keep pace, creating a fragmented environment. While some countries, particularly HICs, are advancing with AI regulations, many LMICs face barriers in developing or enforcing frameworks.

The EU has emerged as a leader in AI regulation with the EU AI Act, the first comprehensive legal framework for AI. The Act categorises AI applications into different risk levels, including High-Risk AI systems, such as those managing critical road infrastructure, which will face strict oversight and compliance requirements. Set to take full effect in 2026, the Act imposes substantial penalties for non-compliance, highlighting the EU's commitment to safety and ethical AI deployment, setting a precedent for other regions and providing a foundation for global AI regulations.

In North America, the regulatory framework is still evolving. The US lacks comprehensive federal AI legislation, though individual states such as California and Colorado have introduced private-sector AI governance laws, expected to influence high-risk AI systems in transport. This approach, which differs from the more regulated approach of the EU can have benefits in terms of AI development and innovation, but may also introduce risks due to lack of regulation. Canada is preparing an AI and Data Act to regulate high-impact AI systems, ensuring ethical deployment and preventing biases, particularly in road planning and service access. In the US, management frameworks, such as those proposed by the National Institute of Standards and Technology (NIST), are adapted for AI applications across sectors, including transportation.

Meanwhile, many LMICs lack AI laws, with only general data protection or privacy laws affecting AI deployment. Countries such as Mexico and Costa Rica are exploring AI solutions but have yet to establish comprehensive governance frameworks. This regulatory uncertainty is compounded by the absence of clear guidelines on AI implementation in the road sector. The delay in AI-specific legislation presents challenges in compliance and risk management. These regions focus on developing digital infrastructure and capacity-building initiatives.

In conclusion, while significant progress is being made in AI legislation, particularly in HICs, a considerable gap remains in regulatory preparedness, especially in LMICs. By 2030, most HICs are expected to have integrated AI regulations in their road sectors, aligned with international standards such as the EU AI Act. LMICs will need to focus on developing regulatory frameworks that support AI adoption while addressing concerns over data security, ethical AI use, and public accountability. Even in the EU, where there has been significant effort to regulate AI developments, there still remains a great degree of uncertainty about how the AI Act will translate into legal requirements for transport specific applications. As greater clarity is gained on these requirements, this will likely dictate the development and uptake of specific AI technologies by NRAs and ROs.

Table 3.2 summarises global AI regulation adoption by region.

3.5. SUMMARY AND CONCLUSIONS

This section has summarised the current state of AI technologies in the road sector, based on findings from the literature. The review highlights key developments, challenges, and the potential trajectory towards 2030. AI has made significant impacts in improving road safety, traffic management, infrastructure maintenance, and asset management, particularly in HICs. These advancements rely heavily on AI-driven systems such as adaptive traffic signal control, predictive maintenance, and ADAS, demonstrating benefits in efficiency, safety, and sustainability.

However, AI adoption in LMICs faces additional barriers, primarily related to financial constraints, inadequate infrastructure, and data quality issues. Despite these challenges, AI solutions are being trialled in LMICs, particularly for traffic monitoring and infrastructure inspection, with promising results in cities where digital infrastructure is more developed.

The literature review indicates that as AI evolves, the road sector will see broader integration by 2030. In HICs, AI will drive innovations in smart mobility, climate resilience, and predictive maintenance, while in LMICs, AI will enhance infrastructure management and resilience to climate change. Addressing challenges related to data reliability, regulations, and capacity building will be critical for AI’s potential. For further details on the findings of the literature review, an extended version is included in Appendix B.

Table 3.2: Global AI regulation adoption by region.

Region	Matured	Developing	Nascent
Europe	Europe leads in AI regulation with the EU AI Act, classifying AI by risk and enforcing strict compliance for high-risk systems. Countries such as Germany, the UK, France, and other EU members have strong AI governance frameworks.	Some EU nations are implementing these frameworks, though the process may vary slightly between member states.	No notable regions here.
North America	The U.S. and Canada are advancing AI regulation with initiatives such as the NIST AI Risk Management Framework and Canada's AI and Data Act, guiding AI adoption in industries such as transportation.	Some U.S. states have AI laws, but they are not yet standardised nationwide.	Limited, though some areas, particularly smaller or less-regulated ones, are still in the early stages.
Asia	Japan and Singapore are leading AI initiatives in transport, smart cities, and infrastructure management.	China has ambitious AI plans, but its regulations are still developing, with inconsistent enforcement across regions.	Many developing Asian countries, especially in Southeast and South Asia, are still in the early stages of AI governance due to limited resources and infrastructure.
Africa	Limited examples exist, with ongoing projects such as AI guidelines from the African Union, but these are not yet binding regulations.	Some countries, such as South Africa, show interest in AI, but regulations are still in the conceptual stage.	Most African countries, especially in Sub-Saharan Africa, are in the early stages of developing AI legislation and governance.
Latin America	Brazil has made progress with digital governance frameworks, though not fully focused on AI-specific regulations.	Countries such as Argentina, Chile, and Colombia are developing AI policies, but regulatory frameworks are still forming.	Other countries in the region are exploring AI in the road sector, with limited regulatory frameworks.
Oceania	Australia is making significant progress in AI regulation with a national strategy and frameworks covering sectors like transportation.	New Zealand is developing AI policies but lags behind Australia.	No notable regions here.

4. SUMMARY RESULTS FROM STAKEHOLDER ENGAGEMENT

Section highlights



Presents findings from a high-level survey capturing stakeholder insights on AI adoption, road sector digitalisation, anticipated applications, and key challenges affecting the road sector up to 2030. This section summarises key findings from the stakeholder engagement. For full details, see Appendix C.



Summarises in-depth perspectives from targeted stakeholder interviews, providing qualitative insights into organisational readiness, AI implementation barriers, and opportunities within the sector.

The stakeholder engagement process was crucial in gathering insights from key actors in the road sector, enhancing the understanding of AI technologies' current and future roles. It involved two main activities: an international survey (Section 4.1) and in-depth interviews (Section 4.2). The survey provided a global overview of AI applications in the road sector along with challenges and opportunities, while allowing key stakeholders to be identified for interviews. The interviews, with professionals directly involved in AI implementation, were largely focused on documenting detailed case studies and explored challenges and opportunities in both HICs and LMICs. This approach offered a comprehensive understanding of AI adoption factors and shaped the study's recommendations. Survey findings are compared with interview insights in Section 4.3, and Section 4.4 discusses conclusions, implications, and alignment with the literature review. This section provides a high-level summary of the results from the stakeholder engagement, and full details can be found in Appendix C.

4.1. SURVEYS

The stakeholder engagement process commenced with a high-level survey designed to gather insights into AI applications, challenges, and projected future implementation within the road sector. The findings provide an overview of the sector's technological maturity, AI adoption, and expected benefits and barriers to AI integration by 2030. The objective was to elicit feedback from key stakeholders as part of a broad horizontal scan across all aspects of the road sector, encompassing all life cycle stages and infrastructure assets.

The survey, developed in consultation with the PIARC POT, included interrelated questions to assess the current and future levels of AI technology in the road sector. It also aimed to evaluate the level of digitalisation across countries and identify disparities within different parts of the road network in the same country. The survey questions and raw data are provided in Appendix C.

ROD developed a list of key stakeholders in consultation with the POT and the survey was circulated amongst the intended respondents who were chosen from a list of PIARC and ROD contacts. The recipients of the survey were primarily NRAs, ROs, local and municipality authorities, however, there were also respondents from research institutions, technology providers and other experts in the field of AI and road infrastructure.

The survey included 29 questions, with the initial questions used to collect information aimed at understanding respondents' organisations, their roles, and the key challenges they face. Participants were then asked about the technological infrastructure in their regions and the level of AI integration in their road sector operations.

The survey explored current and planned AI applications up to 2030, focusing on AI's role in activities such as asset management, road safety, and maintenance. Participants provided details of specific AI-related projects or pilot studies. Data-related questions assessed the availability, quality, and accessibility of key data types (e.g., traffic data, pavement condition) supporting road sector decisions. The survey also examined the legislative and regulatory context of AI technologies, and respondents discussed barriers and challenges to AI implementation, including data privacy, financial constraints, and the impact on human expertise. The survey concluded with an opportunity for additional feedback and further engagement in the study.

The survey was developed in English, French, and Spanish. All three versions were produced using the SurveyMonkey platform (SurveyMonkey, 2024). ROD received 62 responses: 50 in English, 4 in French, and 8 in Spanish. The results from all are summarised in the following sections and Appendix C.

The majority of respondents (45%) were from NRAs, followed by public administration bodies and research institutions (11% each). State or provincial road authorities accounted for 10%, while fewer than 5% were from local authorities, engineering and design firms, technology providers, and other sectors. Socio-economically, the majority of responses (81%) came from HICs, with UMICs and Lower MICs+LICs representing 13% and 6%, respectively. Due to the limited responses from Lower MICs and LICs, their data were combined and presented as Lower MICs+LICs. A map showing the geographical and socio-economic spread of respondents is shown in Figure C.2, in Appendix C. The following section presents the key findings and a summary of the survey results.

4.1.1. Key findings and summary of survey results

The survey results reveal a substantial disparity in the adoption and maturity of AI applications between HICs and LMICs. While AI is widely deployed in advanced economies, its implementation in LMICs remains in an early, experimental stage, hindered by barriers that differ significantly from those in wealthier nations.

4.1.1.1. AI adoption

Regarding AI adoption in the road sector, the responses revealed that advanced AI ecosystems have primarily been established in HICs, typically supported by well-developed digital infrastructure. In these regions, systems such as ITS have become integral to traffic management and safety initiatives. In contrast, AI adoption in LMICs remains fragmented and is often limited to pilot projects or specific applications. AI systems are generally restricted to basic road activities, such as vehicle counting and incident detection, with predictive analytics and more advanced applications being rare.

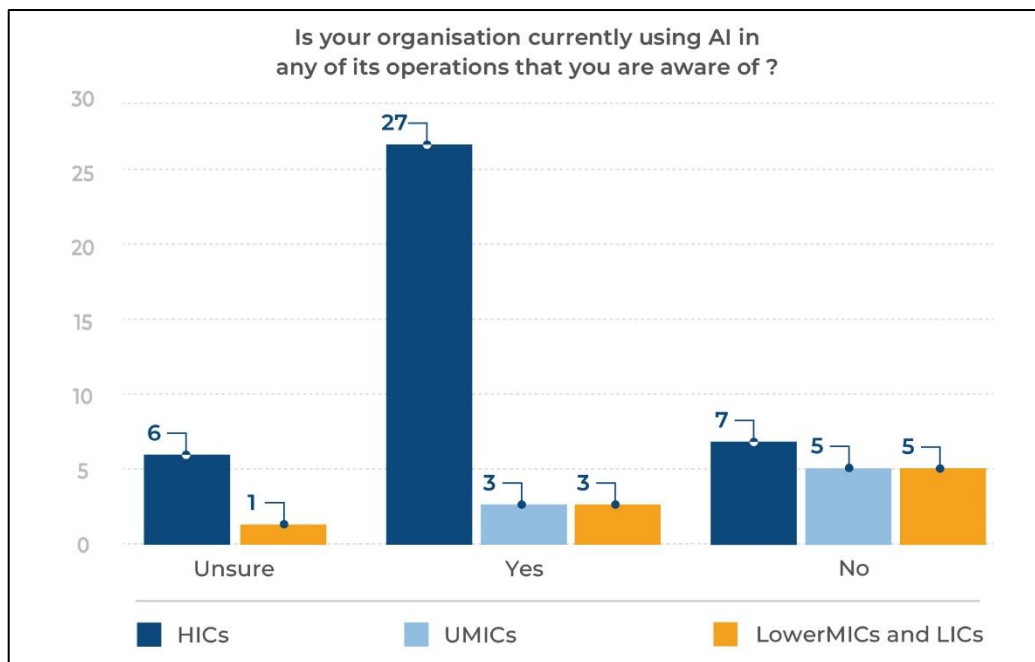


Figure 4.1: AI adoption in the road sector between HICs and LMICs.

Figure 4.1 illustrates AI adoption across HICs, UMICs, and Lower MICs+LICs. It shows that 58% of respondents are currently using AI in some capacity within their organisations, with the majority (approximately 47%) from HICs. UMICs and Lower MICs+LICs account for 5% each. In contrast, 30% of respondents reported that their organisations were not using AI technologies, including 20% from HICs and around 13% from each of the Lower MICs+LICs and UMICs, suggesting that barriers to AI adoption persist even in higher-income regions. Additionally, some respondents were unsure of the use of AI within their organisations, suggesting potential gaps in internal communication or awareness about AI usage.

4.1.1.2. Current applications of AI in the road sector

Figure 4.2 summarises the primary AI applications noted by survey respondents. The results show that the most prominent AI application in the road sector is in road operations, traffic management, and incident management, accounting for 30% of responses - 24% from HICs and 3% from Lower MICs+LICs. Asset management follows closely at 20%, with 17% from HICs and 2% from Lower MICs+LICs. Infrastructure inspection and monitoring also make up 20% of responses, with 17% from HICs and 3% from Lower MICs+LICs.

AI's role in road safety was noted by 15% of participants, mostly from HICs (13%) and a smaller share from Lower MICs+LICs (2%). Planning, feasibility studies, route selection, and project appraisal accounted for 13% of responses, with 10% from HICs and 3% from Lower MICs+LICs. Similarly, 13% of respondents highlighted AI in infrastructure maintenance, repairs, and rehabilitation, with 10% from HICs and 3% from Lower MICs+LICs. These findings are largely aligned with the documented literature, however it is noted that there is less emphasis on design and construction applications in the surveys, which is likely explained by the fact that the organisations who would typically carry out these activities (contractors, consultants etc.) were not well represented in the survey. It also highlights the fact that NRAs / ROs are likely to be more aware of

AI technologies which affect the activities which they are directly involved in, such as asset management, inspection, or road safety.



Figure 4.2: Current applications of AI in the road sector.

4.1.1.3. Benefits achieved through AI implementation

Figure 4.3 summarises the areas in which survey respondents indicated that they have achieved benefits through the use of AI, while also quantifying the level of benefit in each area. The survey revealed regional differences in AI benefits across HICs, UMICs, and Lower MICs+LICs. Time savings were most significant in HICs (45%), followed by UMICs (35%) and Lower MICs+LICs (20%), indicating more advanced AI implementation in wealthier nations. Enhanced infrastructure inspection was rated medium to high by 50% of HICs, 30% of UMICs, and 15% of Lower MICs+LICs, suggesting HICs lead in adopting AI technologies e.g. computer vision. AI's role in road safety was recognised by 40%, with 30% from HICs and 10% from Lower MICs+LICs, highlighting greater investment in safety solutions in wealthier countries. In asset management, 25% of HICs reported high benefits, compared to 15% of UMICs and 5% of Lower MICs+LICs, indicating underexplored potential in lower-income nations.

Cost savings were noted by 30% of respondents, with 20% from HICs, 7% from UMICs, and 3% from Lower MICs+LICs, with the majority of these respondents reporting medium to high savings. Network performance improvements were cited by 35%, with HICs (25%) seeing the most impact and 5% from Lower MICs+LICs. AI's effect on maintenance was recognised by 40% in HICs, 30% in UMICs, and 20% in Lower MICs+LICs, showing stronger adoption in higher-income regions. Environmental benefits and decarbonisation received the lowest ratings, with only 10% from HICs and 5% from UMICs, suggesting the application of AI technology to sustainability goals remains underdeveloped. Finally, AI's influence on administrative processes was mixed, with 20% from HICs, 10% from UMICs, and 5% from Lower MICs+LICs.

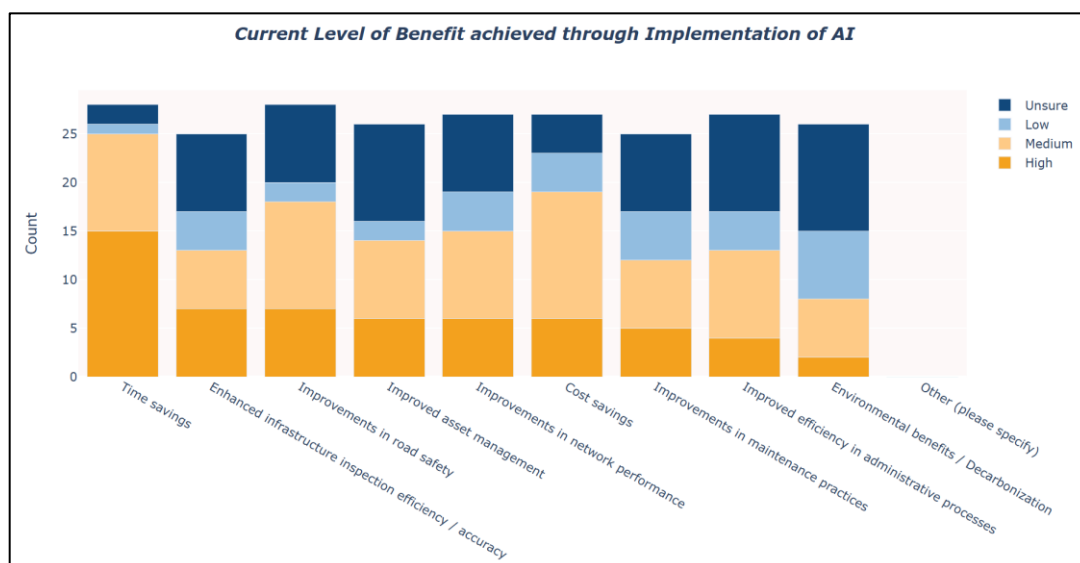


Figure 4.3: Current level of benefit achieved through AI implementation.

4.1.1.4. Future perspectives on AI by 2030

Figure 4.4 summarises the survey respondents' views on the expected uptake of AI in the road sector by 2030. The results indicate a 21% increase in organisations planning to adopt or integrate AI by 2030. Among income groups, 80% of respondents from HICs plan to adopt AI, reflecting strong future adoption in wealthier regions. In contrast, 10% of respondents from UMICs and Lower MICs+LICs expressed similar intentions. These figures suggest AI adoption is more common in higher-income regions, though interest is also present in UMICs and Lower MICs+LICs.

No respondents indicated that they did not intend to adopt AI by 2030, showing universal recognition of its perceived potential. However, 27.5% of HIC respondents and 10% of UMIC respondents expressed uncertainty about their AI plans, suggesting unclear strategies or varying awareness. No respondents from Lower MICs+LICs showed such uncertainty, perhaps, indicating a more defined or prioritised approach to AI adoption, but it is noted that the views of the small number of respondents from these categories may not necessarily be reflective of the overall consensus amongst these countries. In summary, the survey responses on expectations for AI adoption by 2030 reflect a growing global recognition of AI's importance, with the highest adoption plans in wealthier nations. The uncertainty in HICs and UMICs may point to challenges in planning, while Lower MICs+LICs appear more focused in their decision-making.

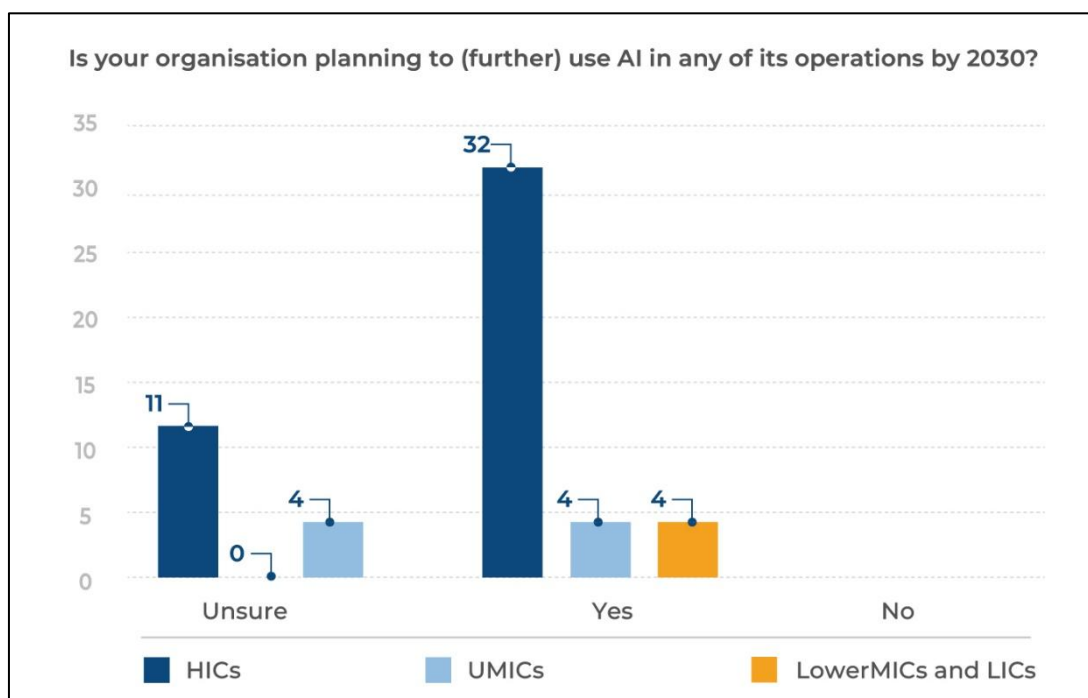


Figure 4.4: Future perspectives of AI in the road sector by 2030.

Figure 4.5 illustrates the areas in which respondents envisage AI adoption in the road sector by 2030. The responses indicate a strong intent to implement AI technologies with road operations, traffic management, and incident management being the most frequently cited activity, followed by asset management. Planning, feasibility studies, route selection, and project appraisal also feature prominently. Infrastructure maintenance and repairs, as well as resilience planning and winter services, are highlighted as key areas for AI use. Environmental impact assessment, tolling, and road design are given less priority. AI adoption in construction-related activities is the least recognised, while strategic and sustainability areas such as policy development and decarbonisation attract limited attention. Again, these may be related to the roles of the survey respondents and not necessarily truly reflective of the views of the industry as a whole.

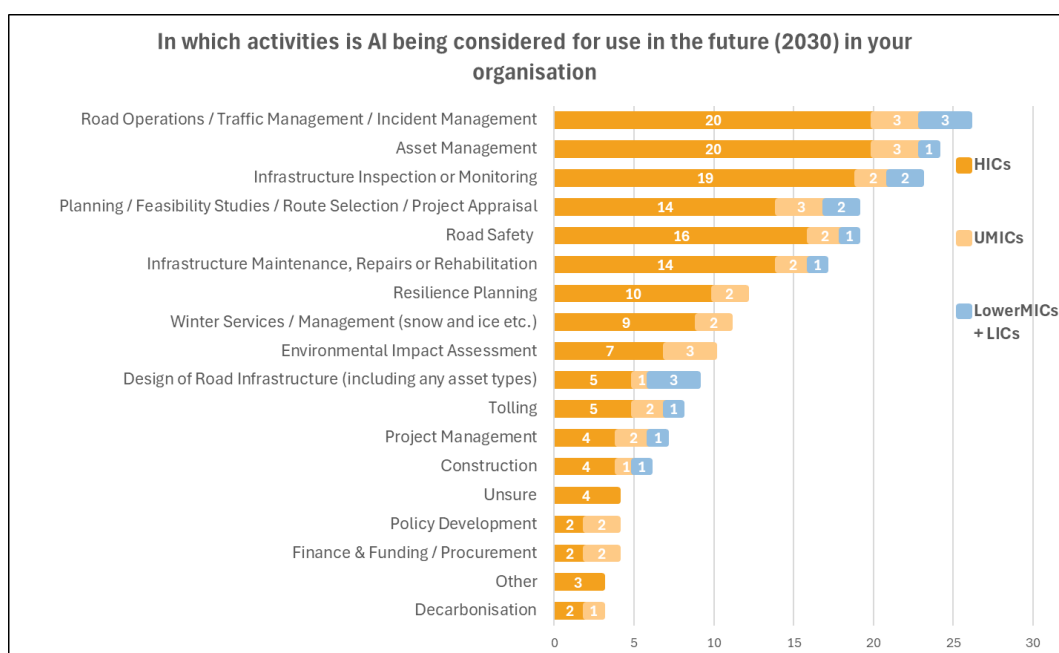


Figure 4.5: Predictions of AI applications in the road sector by 2030.

4.1.1.5. Level of expected benefits from AI by 2030

The survey results show considerable optimism about AI's potential in the road sector (see Figure 4.6). Time savings were indicated to be a key expected benefit, with many rating its impact as high or medium, highlighting AI's ability to optimise processes and improve efficiency. Asset management and infrastructure inspection were also identified as areas where AI could add value through better resource allocation and accuracy. Cost savings and improved network performance were widely acknowledged, with expectations for AI to optimise operations and reduce costs. Positive expectations for road safety and maintenance were also noted, supported by AI's predictive and real-time monitoring capabilities. However, respondents were more cautious about AI's impact on environmental sustainability and administrative efficiency, indicating that while AI's benefits for operational tasks are clear, its role in non-operational areas remains less explored.

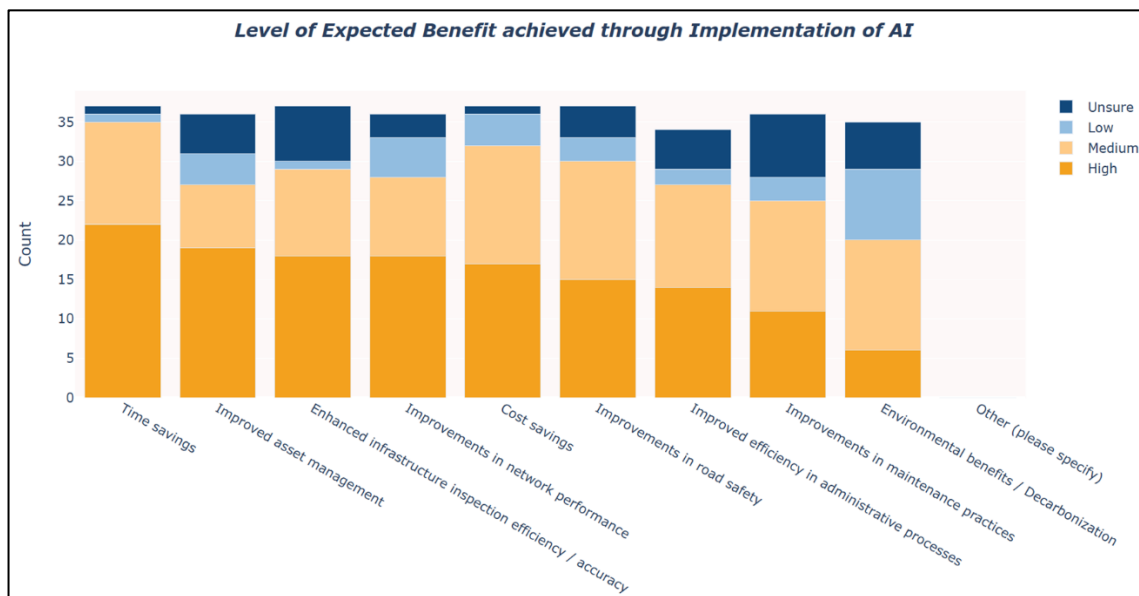


Figure 4.6: Level of expected benefit achieved through AI implementation.

4.1.1.6. Risks, barriers and challenges faced in AI implementation

The survey respondents were also asked to identify key barriers to AI adoption in the road sector, with notable differences in opinions across HICs, UMICs, and Lower MICs+LICs, as illustrated in Figure 4.7 (where Lower MICs+LICs are collectively grouped under the 'LMIC' heading for ease of visualisation).

Data-related issues such as privacy, cybersecurity, and data-sharing constraints were major concerns in HICs and UMICs, where AI adoption underscored the need for secure, reliable data. In contrast, the primary challenge in Lower MICs+LICs was a shortage of skilled personnel, highlighting the need for targeted training in AI. Technical challenges and infrastructure gaps were common across all income groups but most severe in Lower MICs+LICs, where limited ITS infrastructure impedes progress. HICs and UMICs, while facing fewer issues, noted the complexities of AI system integration.

Financial constraints were a significant barrier in Lower MICs, where limited resources hinder large-scale AI projects. In contrast, HICs and UMICs faced fewer financial obstacles due to better access to funding. Legal and regulatory uncertainty, a concern across all regions, complicates AI governance amid rapid technological change. Trust in AI was especially problematic in UMICs, where concerns about reliability, transparency, and biases slowed adoption. Resistance to organisational change, particularly in Lower MICs+LICs, made AI implementation challenging. Additionally, fears of job displacement were most pronounced in Lower MICs+LICs, highlighting the need for upskilling and clear communication.

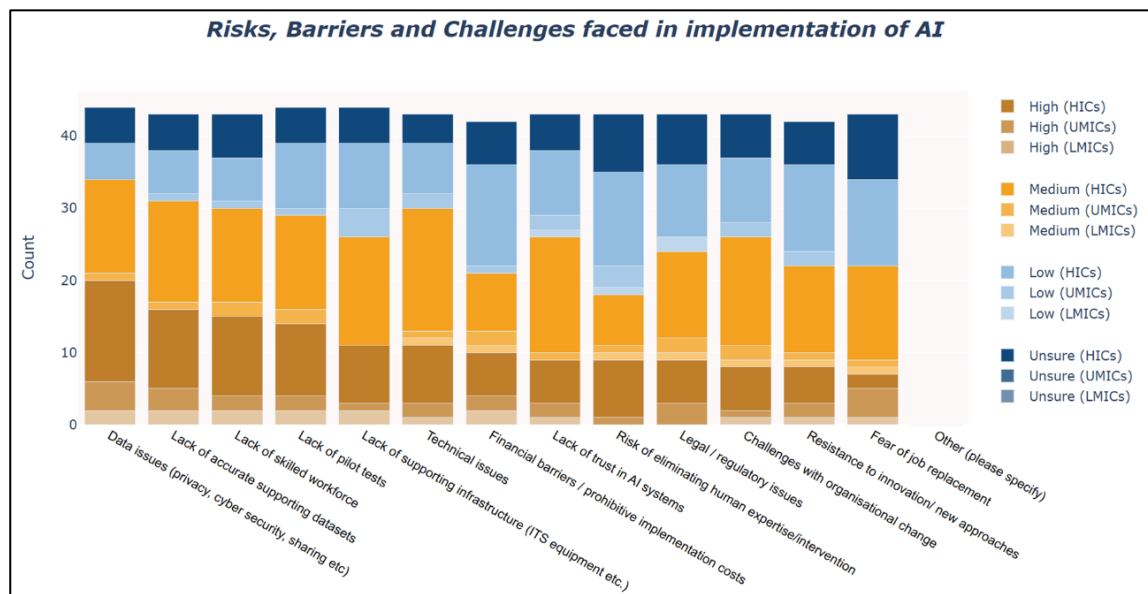


Figure 4.7: Risks, barriers and challenges faced in AI implementation.

4.2. INTERVIEWS

The survey analysis helped to identify key stakeholders in the road sector, who were then invited for interviews. These structured interviews aimed to gather in-depth insights on AI adoption and implementation, focusing on challenges, opportunities, and experiences in different contexts. The interviews included three categories of questions: (1) case studies of AI technology pilots or implementations, (2) general perspectives and challenges of AI adoption in HICs, and (3) opportunities and barriers in the road sector in LMICs.

ROD conducted 8 interviews with 11 stakeholders across 7 countries (3 from HICs, 1 from LICs, 1 from Lower MICs, and 3 working in multiple countries with various incomes), providing valuable global perspectives. The use of segmented questions facilitated focused discussions, allowing stakeholders to share insights on AI applications specific to their regions. A semi-structured approach was employed, with questions shared in advance to ensure thorough preparation. These questions, outlined in Appendix D, guided the conversations and helped gather actionable insights. Table C.2 offers an overview of the conducted interviews.

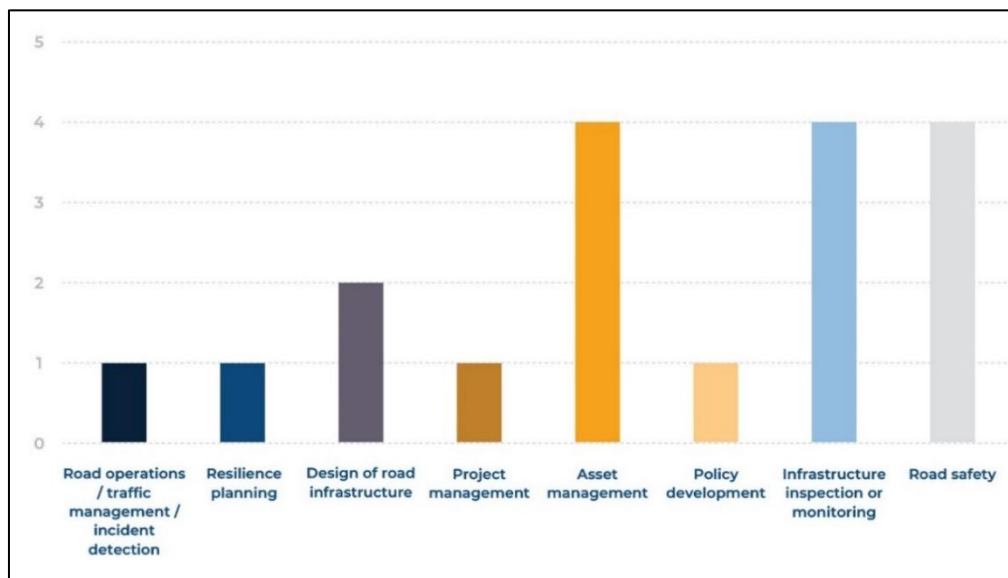


Figure 4.8: Different activities for which interviewees are involved or have implemented AI technologies.

Figure 4.8 illustrates the activities in which interviewees work and in many cases where they have employed AI technologies. There is a clear emphasis on asset management, infrastructure inspection or monitoring, and road safety which were determined to be key areas of interest based on the results of the literature review and the survey.

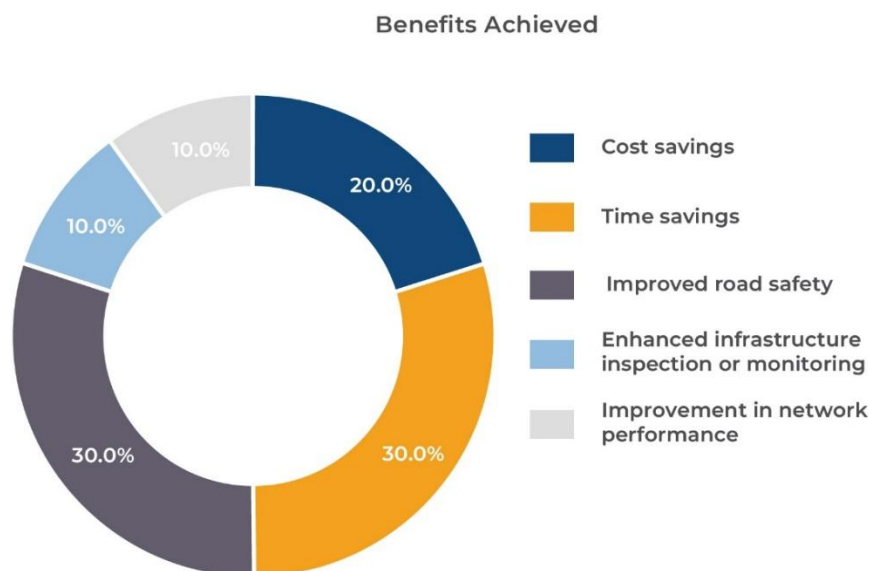


Figure 4.9: Key benefits noted by interviewees in their AI implementation.

Figure 4.9 summarises the key benefits achieved through the use of AI technology, as indicated by the interviewees. It is important to note that the majority of interviewees had been chosen because they had been involved in the deployment of AI technologies in the road sector, so the benefits noted by the interviewees provide a detailed reflection of the measured benefits in the areas of activity in which they were working. Time savings and improved road safety stand out as the primary advantages, each accounting for 30% of the overall outcomes. This is followed by cost savings, which make up 20%. Enhanced infrastructure inspection or monitoring and improvements

in network performance each contribute 10%, underscoring AI's role in optimising resource management and performance metrics.

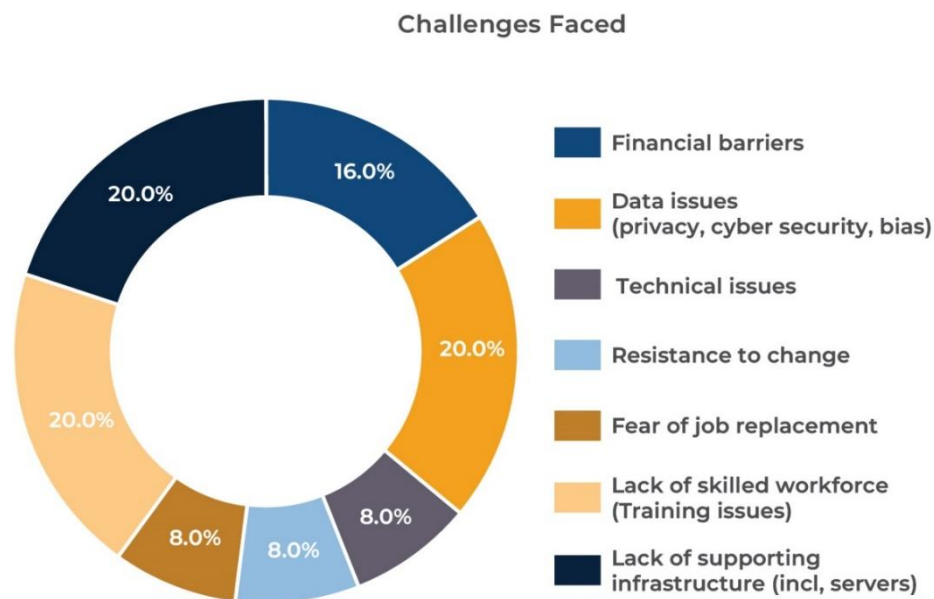


Figure 4.10: Challenges faced by interviewees during the implementation of AI technologies.

The key challenges in implementing AI technologies, as reported in the interviews, are shown in Figure 4.10. The most prominent obstacles include a shortage of skilled workforce, insufficient infrastructure, and data-related concerns - such as privacy, cybersecurity, and bias - each representing 20% of the issues. Financial barriers account for 16%, while technical difficulties, resistance to change, and concerns about job replacement, though noted, are less significant, each contributing 8% to the overall challenges.

The interviews with HICs also highlighted key factors in implementing AI. One key discussion centred on the choice between using third-party AI systems via Software as a Service (SaaS) or developing in-house AI. This decision affects scalability, control, and long-term costs. SaaS offers low initial costs and ready-to-use solutions, while in-house systems provide greater customization. Other factors include technical expertise, application complexity, data security, and budget. For instance, the Lanternn incident detection system operates through SaaS, offering benefits for road authorities that might be hard to replicate with an in-house system. In contrast, Sydney's SCATS tool, originally developed for local traffic optimisation, demonstrates the advantages of an in-house system, offering high customisability before becoming commercially available globally.

An interviewee from an LIC highlighted the need for a cultural shift in adopting AI technologies. Government and organisational leaders can drive this change, but they must be guided by technical expertise and the ability to demonstrate AI's benefits. This issue is relevant in both HICs and LMICs. Pilot projects on critical issues such as road safety can demonstrate AI's advantages, fostering innovation and broader acceptance. Moreover, sustainability and climate challenges are particularly pressing for LMICs, which often lack the resources to address climate change. Infrastructure resilience is crucial for mitigating the impacts of extreme weather or climate-related events in these countries. Given limited resources, LMICs must optimise data collection for asset management, focusing on the right data. Typically, advice on data collection strategies is sought

from consultants from outside of LICs, however, these foreign consultants often lack local knowledge, making it harder to align data collection with community needs. Local expertise is essential for maximising AI system effectiveness in these regions.

4.3. COMPARISON OF SURVEY AND INTERVIEW FINDINGS

Comparing the findings from the survey and interviews highlights a number of similarities, but also identifies some differences in views on AI adoption in the road sector. There is strong alignment in the recognition of the potential benefits of AI, and in the focus on applications in road operations, traffic management, and infrastructure inspection. The survey found 30% of respondents involved in road operations, while interviews emphasised use cases in asset management, road safety, and infrastructure monitoring. These commonalities highlight AI's role in improving operational efficiency and safety across both HICs and LMICs. However, it is noted that the perspective of the interviews is skewed towards the use of AI in these particular areas because a number of the interviewees were specifically chosen based on the fact that they had actively implemented AI technologies in these activities.

Another shared finding is the recognition of varying AI maturity and adoption levels across socio-economic groups. The survey showed a clear divide, with HICs demonstrating more advanced AI integration and LMICs limited to pilot projects. Interviews confirmed this, with HIC stakeholders reporting more widespread implementation and LMIC respondents highlighting challenges such as infrastructure gaps and limited skilled labour. Notably, interviewees from LMICs emphasised the need for a cultural shift towards AI adoption, a point less emphasised in the survey but consistent with broader trends.

Despite these similarities, key differences also emerge. The survey, with its broader scope, offered a high-level quantitative view of AI's benefits and barriers, while the interviews provided more detailed qualitative insights (and also quantitative benefits for many of the case study examples). For example, both identified data-related issues as significant barriers, but the survey focused on privacy and cybersecurity concerns, particularly in HICs and UMICs. In contrast, the interviews explored contextual barriers in LMICs, such as a shortage of local technical expertise and infrastructure gaps.

The survey presented a more optimistic view of AI's future in the road sector, with HIC respondents keen to expand AI adoption by 2030. In contrast, interviews highlighted caution in LMICs, where financial and political challenges hinder AI implementation. HICs also showed a strong preference for bespoke in-house AI solutions, unlike the less common use of third-party services mentioned in the survey.

4.4. CONCLUSIONS, IMPLICATIONS, AND ALIGNMENT WITH LITERATURE

The findings from the stakeholder engagement, based on surveys and interviews, are well aligned with those from the literature review. The stakeholder engagement phase enabled additional detail and opinions to be elicited from those working in the road sector on AI adoption challenges and opportunities. These insights suggest a global consensus on AI's potential but highlight the need for region-specific strategies.

The literature review highlights rapidly advancing AI adoption, especially in HICs, where technologies such as adaptive traffic signals, predictive maintenance, and ADAS have become well developed and tested technologies. These applications align with survey and interview findings,

where respondents from HICs reported widespread AI use in road operations, traffic management, and asset management. The optimism expressed about AI's benefits by 2030 mirrors the literature's conclusions on its transformative potential. Both the literature and stakeholder insights support AI's growing role in improving efficiency, safety, and sustainability, with respondents citing time savings, safety improvements, and better infrastructure monitoring as key benefits.

The literature review highlights significant barriers to AI adoption in LMICs, where AI integration is still in the experimental stages. Survey and interview results confirm this, with LMIC stakeholders citing challenges such as limited infrastructure, poor data quality, financial constraints, and a lack of skilled personnel. This underscores the gap between the advanced AI ecosystems in HICs and the emerging applications in LMICs, suggesting that adoption in these regions faces greater obstacles. The shortage of local expertise and the need for a cultural shift towards AI, as discussed in the interviews, adds further complexity to AI integration in LMICs.

A key implication of these findings is the need for tailored approaches to AI deployment across regions. The literature review highlights the importance of addressing financial, data, and regulatory barriers, issues especially pronounced in LMICs, as confirmed by the survey and interview data. There is a clear need for international collaboration, knowledge-sharing, and development of scalable, cost-effective AI solutions for lower-income countries. Additionally, the need for clear regulatory frameworks, as noted in the literature, is reinforced by survey responses, with stakeholders expressing uncertainty about AI governance in HICs.

5. CASE STUDIES

Section highlights



Brief description of 7 different case studies outlining pilots, trials, or full-scale implementation of AI technologies in the road sector. The case studies focus on infrastructure inspection, road safety, and incident management. This section summarises key findings from the case studies. For full details, see Appendix E.



Key findings of each case study across four categories, i.e., technology and innovation, objectives and goals, key outcomes and results, challenges, and lessons learnt.

This section presents a series of case studies that demonstrate the practical application of AI in the road sector. These case studies, drawn from diverse geographical regions and varying socio-economic contexts, highlight the transformative potential of AI in enhancing road safety, infrastructure management, and operational efficiency. Each case study provides insights into the technologies employed, the challenges faced, and the outcomes achieved, offering valuable lessons for the broader AI implementation solutions. By examining these real-world examples, this section aims to inform future strategies for integrating AI into road infrastructure management and safety systems globally. This section provides a high-level summary of seven different case studies and full details of each case study can be found in Appendix E.

5.1. OUTLINE OF CASE STUDIES

The case studies illustrate the varied approaches to integrating AI into road infrastructure management, safety, and maintenance, offering valuable lessons for future implementations. The case studies are focused on some of the key areas for which AI has been adopted in the roads sector, and aim to provide examples of the implementation process, the challenges experienced and how they were overcome, and the benefits achieved.

The EyeVi platform in Oslo applies AI-driven image recognition to digitise road defects, facilitating more efficient defect detection and prioritisation for maintenance. Similarly, the COWI virtual inspection platform in Denmark utilises AI for remote bridge condition assessments, reducing the need for manual inspections and improving safety through predictive maintenance capabilities. In Lima, Peru, Lanternn by Valerann utilises data fusion and AI to combine multiple data sources which enables enhanced real-time detection of incidents on the network. Acusensus in New South Wales, Australia, uses AI-powered cameras to monitor traffic law enforcement, improving road safety by detecting violations such as speeding and seatbelt non-compliance in real-time.

The iRASTE project in India integrates AI to predict and monitor road safety, reducing accidents through real-time hazard detection and intervention. Meanwhile, TRL's project on unpaved roads uses satellite imagery and AI to monitor remote road conditions, enabling proactive maintenance in areas where traditional inspection methods are difficult or costly. Lastly, Víasegura in South America uses AI to classify roads based on their level of safety, allowing for targeted interventions in high-risk areas to improve road safety and reduce accidents.

Together, these case studies demonstrate the diverse and significant ways in which AI is already transforming road infrastructure management, safety, and operations. They underscore AI's potential to optimise road maintenance, improve safety, and drive more efficient resource allocation, providing valuable insights for future AI implementations globally. For full details of each case study, please refer to Appendix E.



Figure 5.1: EyeVi platform - digitalisation of defects on Oslo's urban road network.

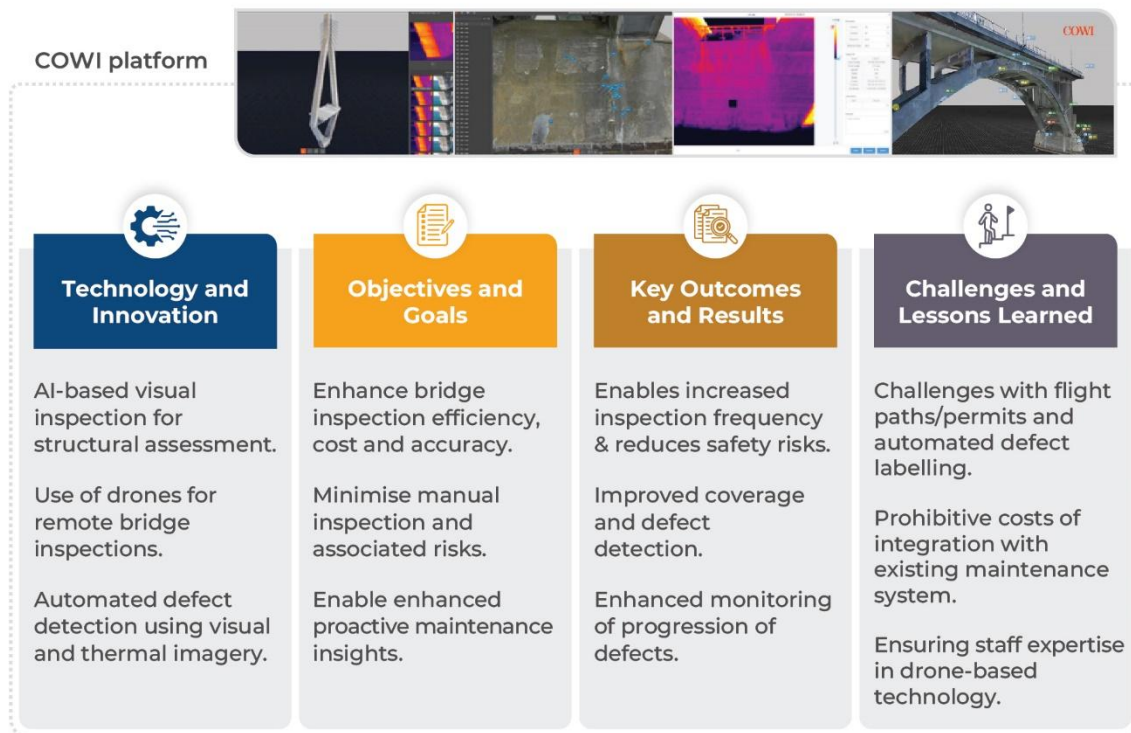


Figure 5.2: COWI virtual inspection platform - condition assessment of Faroe bridges.



Figure 5.3: Lanternn by Valerann used for incident detection in Lima, Peru.



Figure 5.4: Acusensus used for detecting mobile phone & seatbelt offences in New South Wales, Australia.

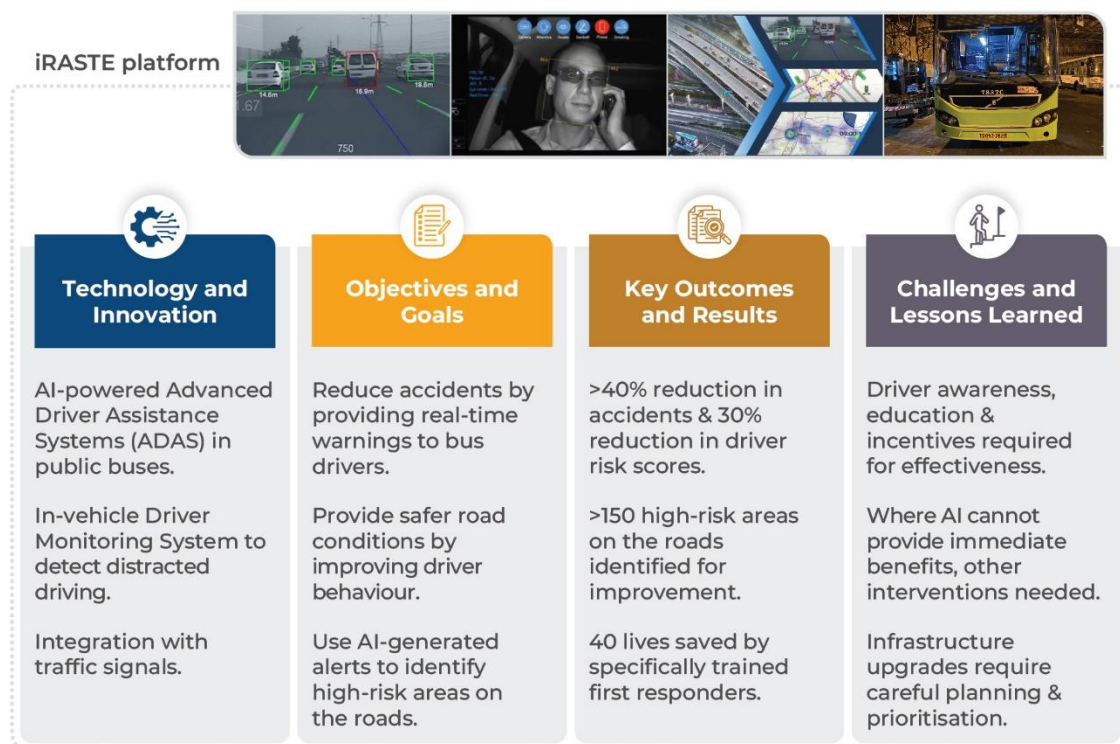


Figure 5.5: iRASTE project focused on using AI for improving road safety, India.



Figure 5.6: TRL - Monitoring of unpaved road conditions in Africa using satellite imagery and AI.

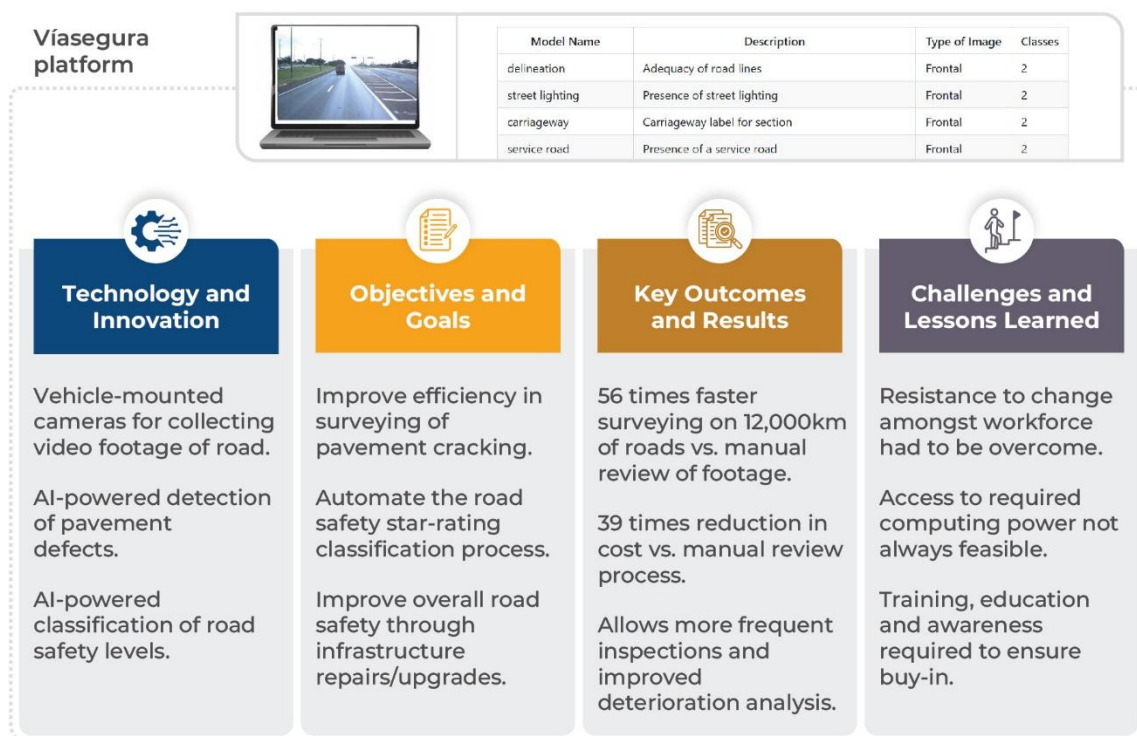


Figure 6.7: Viasegura – Automated classification of road safety and pavement condition in South America.

5.2. CONCLUSIONS

The case studies presented above, and further detailed in Appendix E, provide real examples of how AI is already transforming the activities of NRAs and ROs across the globe. These examples highlight the transformative potential of AI in enhancing road safety, improving infrastructure management, and optimising operational efficiency. The case studies illustrate that AI is being effectively employed across various regions, from high-income countries to lower-income countries, showcasing its adaptability to different socio-economic contexts and technological environments.

Key outcomes, such as improved traffic management, proactive maintenance, and enhanced safety measures, underline the value of AI in addressing challenges faced by road authorities worldwide. However, the case studies also reveal common challenges, including data integration, privacy concerns, and the need for skilled personnel. These barriers highlight the importance of tailored solutions, continuous training, and robust governance frameworks to facilitate successful AI adoption.

In conclusion, the case studies not only provide practical insights into the current state of AI implementation but also underscore the need for strategic planning, collaboration, and investment in AI technologies to fully realise their potential. They also provide examples for other NRAs or ROs to learn from documented examples of AI implementation and to better understand the implementation challenges and the benefits which are being achieved. By learning from these examples, road authorities and stakeholders can better navigate the complexities of AI integration, ultimately improving road safety, infrastructure sustainability, and operational performance globally.

6. SUMMARY OF AI USE IN THE ROAD SECTOR

Section highlights



A summary of the present implementation of AI technologies within the road sector, detailing the diverse applications and variations in adoption across countries with different income level, alongside a vision for AI utilisation by 2030.



An examination of existing regulatory structures governing AI use in the road sector, highlighting the disparities between HICs and UMICs, LowerMICs & LICs, as well as the evolving nature of these frameworks.



An analysis of the barriers hindering AI adoption, such as infrastructural limitations and regulatory uncertainties, juxtaposed with the potential benefits of AI integration.

This section builds upon the findings from the literature review, stakeholder engagement and the detailed case studies to outline the current application of AI in the road sector (the “As-Is” scenario). Additionally, the projected AI landscape for 2030 (the “To-Be” scenario), formulated based on research insights, is presented and analysed.

6.1. “AS-IS” SCENARIO FOR AI IMPLEMENTATION IN THE ROAD SECTOR

6.1.1. Current state

The findings of this research study indicate that AI-based technologies are already being used within the road sector. There is also a vast body of research and development focused on the application of AI-based methods to enhance capabilities in various activities within the remit of those working in the road sector. Findings also indicate that AI use is not only limited to HICs, where funding is more readily available and enabling infrastructure is often better developed, it is also being adopted by countries falling within the LMIC categories. Despite this, it is clear that the current state of AI implementation in the road sector exhibits significant variation across countries, depending on their income levels, infrastructure capabilities, and regulatory frameworks. Many HICs are at the forefront of adopting AI technologies, primarily due to better access to financial resources, existing infrastructure, and a developed regulatory environment. However, LMICs are showing emerging interest, albeit often facing barriers in realising full AI integration in the road sector.

6.1.2. Most commonly used AI technologies

A wide array of AI-based technologies have been adopted within the road sector, though certain key technologies have seen more widespread use across countries with varying income levels. These technologies are summarised in Table 6.1. It is noted that the use of AI algorithms in computer vision or video analytics is by far the most commonly observed technology, covering a range of applications in the road sector. However, ML algorithms, AI predictive analytics software, and data fusion techniques are frequently employed in conjunction with computer vision and video analytics, serving as the enabling technologies that underpin the broader application of AI within

the road sector. These tools enhance the capability of computer vision systems by providing advanced data processing, pattern recognition, and predictive modelling functionalities, enabling more accurate, efficient, and scalable solutions for e.g. complex infrastructure and traffic management challenges.

Table 6.1: Most commonly used AI technologies in HICs and UMICs, Lower MICs, LICs. They are presented in descending order. First is the most common.

HICs	UMICs, LowerMICs, LICs
Computer vision; cameras; drone-based remote sensing	Computer vision; cameras; drone-based remote sensing
Machine learning (data-driven) algorithms; AI predictive analytics software; data fusion	Machine learning (data-driven) algorithms; AI predictive analytics software; data fusion
Augmented reality; virtual reality; mixed reality	
Automated robots/ machinery	

6.1.3. Most common applications of AI in the road sector

In terms of the activities for which AI-based technologies are most commonly being adopted, a number of recurring applications were observed, as summarised by the ‘As-Is’ Scenario illustrated in Figure 6.1.

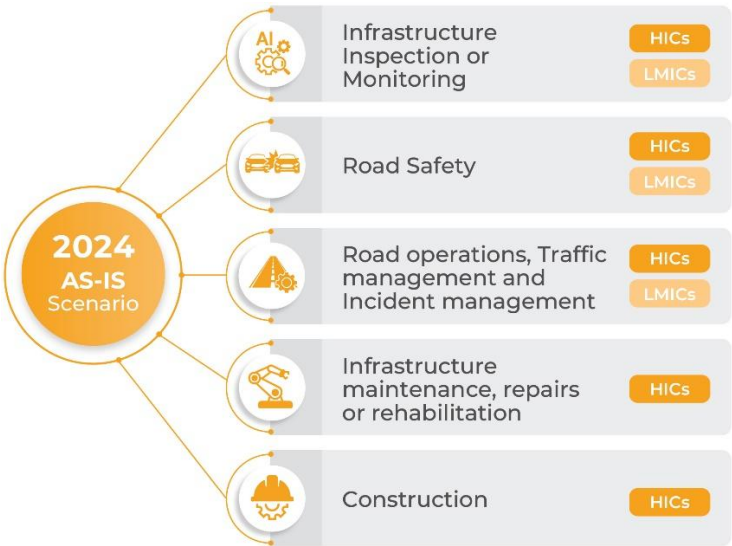


Figure 6.1: Current status of AI use in the road sector (As-Is Scenario).

It is worth noting that, with the exception of integrating AI-based technologies in the design and construction process, HICs and LMICs have seen AI adoption for completion of similar tasks. However, the approach and overall objectives may differ. For example, in HICs, automated

inspection of infrastructure inspection & condition monitoring is primarily targeted at optimising efficiency of decision-making for network-wide asset management. In LMICs, however, it has been observed that the collection of similar information is being used to identify the presence of different types of roads, or infrastructure elements and to classify them from a safety perspective. To give the 'As-Is' Scenario some context related to the benefits being achieved through AI, Figure 6.2 provides an overview of some primary areas where benefits are being achieved through the use of AI already.

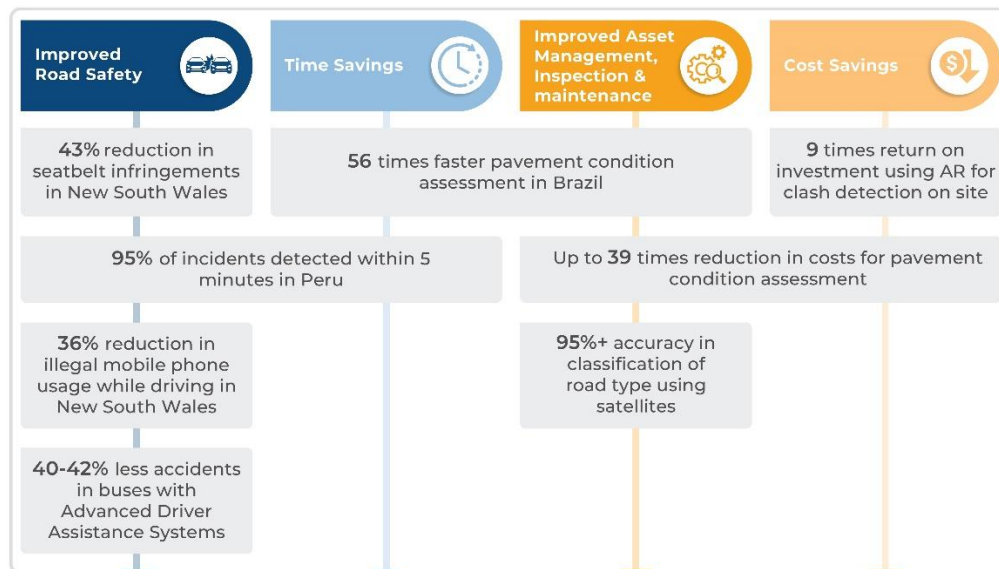


Figure 6.2: Summary of some key benefits observed through AI deployments in the road sector.

6.1.4. Legislation and governance

The overarching findings of this research indicate that although some relevant standards and legislative requirements are already in place which are relevant to the use of AI, there are very few clear examples of guidelines or legislative requirements for AI use in the roads sector. Existing practices for legislation and governance of AI by those working in the roads sector typically relate to data-privacy or data-security laws (e.g. GDPR in the EU) which have been implemented before the recent widespread AI adoption. Despite the relevance for AI, these have not specifically been developed for AI, and those which are specific to AI are still in their infancy. As such, these are only in the early stages of adoption in HICs, and are not yet developed for most LMICs. At present, there is little evidence of how such legislative requirements are affecting national policies, governance or regulation of AI specifically for public bodies operating road networks or for private entities involved in the provision of services within the road sector. However, this is expected to change in the coming years due to the various ongoing efforts to develop AI-specific regulatory frameworks to help regulate the rapidly growing AI adoption across all industries.

Among HICs, the U.K., Canada, the U.S. and several EU countries are leading AI adoption efforts, often citing the use of international standards such as ISO certifications and compliance with regulations such as the EU AI Act. For instance, the UK's focus on maintaining adherence to international standards suggests an advanced approach to risk mitigation, particularly in ensuring safety and reliability of AI systems in road infrastructure. In Canada, Transport Canada follows policies overseen by the Digital Services and Transformation Office, indicating a structured AI

adoption framework. Similarly, in the U.S., several federal and state-level initiatives are underway. While some sector-specific initiatives in the road sector may lack detailed risk mitigation strategies, there are multiple government directives and guidance around risk management practices that are cross-industry and agency. Examples include the NIST AI Risk Management Framework (NIST, 2024) and the White House memorandum “Advancing Governance, Innovation, and Risk Management for Agency Use of AI.” (White House, 2024). These frameworks provide comprehensive risk management approaches that can guide AI adoption across various domains, including the road sector.

In contrast, UMICs such as Mexico and Costa Rica have shown interest in AI but lack the same level of risk mitigation strategies or comprehensive regulatory frameworks seen in HICs. Mexico, for example, has set out general principles for the use of AI within its federal public administration but provides no explicit guidelines for the road sector. Similarly, Costa Rica shows an interest in implementing AI-based solutions, such as video cameras for detecting road surface deterioration, but lacks clarity on how AI will be integrated systematically across the road network.

Lower MICs such as Tanzania exhibit even more nascent stages of AI adoption, with policies or strategies either unclear or underdeveloped. Tanzania, while confirming the existence of AI policies, does not offer detailed information about how AI technologies are being managed in its road sector. This gap between awareness and implementation is a common theme in LICs and Lower MICs, where infrastructural limitations and financial constraints present substantial barriers to adopting sophisticated AI technologies.

The survey results highlighted a significant disparity in AI adoption and implementation within the road sector, with higher-income nations progressing considerably further than their lower- and middle-income counterparts, despite still being in the early stages of implementation. While HICs possess the regulatory frameworks, collaborations, and resources necessary for AI integration, LICs face considerable challenges, with few clear examples of successful implementations.

6.1.5. Future directions

Looking forward, the future of AI implementation in the road sector will likely be shaped by advancements in legislation, international collaborations, and investment in technology and infrastructure. HICs are expected to continue leading the way, building on established AI policies and robust governance structures. The EU AI Act is a significant driver for AI regulation in Europe, with countries such as Austria, Denmark, and Finland indicating that future legislation will likely align with this Act. By 2026, requirements for “high-risk” systems under the EU AI Act will come into force, and will have legal implications for road operators in the EU who are utilising AI-based technologies. As AI technology advances, regulatory frameworks will need to evolve to manage new challenges, such as data privacy, bias in AI systems, and the ethical implications of autonomous decision-making in road infrastructure management.

For LICs and Lower MICs, the focus will need to be on creating foundational computational and communication infrastructure that can support AI technologies. Uganda, for example, plans to benchmark its AI practices against international road agencies while developing internal guidelines that consider ethical and societal implications. This suggests that while these nations may lag behind in current AI implementation, there is a concerted effort to catch up through the adoption of best practices and international standards. Moreover, LICs and Lower MICs have the unique potential to leapfrog older systems by directly adopting modern AI-based technologies, bypassing

some of the incremental steps taken by HICs. This approach can enable faster adoption of cutting-edge solutions without the need to modernise legacy systems.

Investing in capacity building is another crucial direction for future AI implementation. Countries such as Uganda and Ireland highlight the importance of upskilling professionals and ensuring that there is sufficient expertise to manage AI technologies effectively. In LICs, this will require significant investment in education and training, as well as partnerships with international institutions that can provide technical support.

Finally, the integration of AI with other emerging technologies, such as autonomous vehicles, will be a key area of focus in the coming years. As Canada notes, the nexus between AI in vehicles and road infrastructure will become increasingly important, with AI playing a critical role in ensuring road safety and optimising traffic flow. Moreover, global initiatives to harmonise AI implementation across different regions could lead to a more standardised approach, reducing fragmentation and fostering innovation in AI-driven road management systems.

In conclusion, while the current state of AI in the road sector varies significantly by country, the future holds promise for wider adoption, particularly as countries develop the necessary regulatory frameworks, infrastructure, and expertise to fully harness AI's potential in improving road safety, maintenance, and traffic management.

6.2. “To-Be” VISION FOR AI IN THE ROAD SECTOR IN 2030

The future vision of AI implementation in the road sector by 2030 reflects the rapid technological advancements, increased regulatory maturity, and growing commitment to smart infrastructure. The significant body of research and development focused on applying AI methods to the road sector indicates that AI implementation-based technologies will continue to grow at a rapid pace. While this vision represents well-informed projections based on current trends and stakeholder insights, it is important to acknowledge the inherent uncertainty in forecasting the future. Technological advancements, policy developments, and global events may significantly alter the 2030 landscape, and as such, this vision should be considered as a best-guess scenario rather than a definitive outcome.

The global vision for AI in the road sector encompasses enhancing safety, sustainability, and operational efficiency. AI technologies are anticipated to revolutionise traffic management through real-time analytics, optimise maintenance schedules with predictive diagnostics, and bolster road safety through advanced monitoring systems. These developments aim to create interconnected and adaptive transport systems tailored to diverse regional needs, ensuring equitable access to AI-driven solutions. International collaboration will also play a critical role in achieving harmonised standards and addressing socio-economic disparities in AI adoption.

The significant body of research and development focused on applying AI methods to the road sector indicates that the implementation of AI-based technologies will continue to grow at a rapid pace. This vision aligns with the varying levels of development, infrastructure capabilities, and regulatory preparedness across different income groups. Although each group faces unique challenges and opportunities, the overall goal is to utilise AI to improve road safety, optimise traffic management, enhance predictive maintenance, support sustainable infrastructure development and introduce efficiencies across all life cycle stages of roads.

The vision for AI implementation in the road sector by 2030 reflects a broad spectrum of goals and challenges across countries with different income and technology readiness levels. HICs are expected to progress towards integrated AI systems in many areas, while UMICs will likely focus on scalable and cost-effective solutions. Lower MICs will prioritise targeted applications and foundational regulatory frameworks, and LICs will work on laying the groundwork for future AI adoption, or identifying low-cost solutions which can have a big impact.

6.2.1. Expected applications of AI technology by 2030

The 'To-Be' Vision for AI adoption in the road sector is summarised in Figure 6.3, which indicates the expected integration of AI for different activities in 2030. The following subheadings discuss the expected landscape across countries from different income categories.

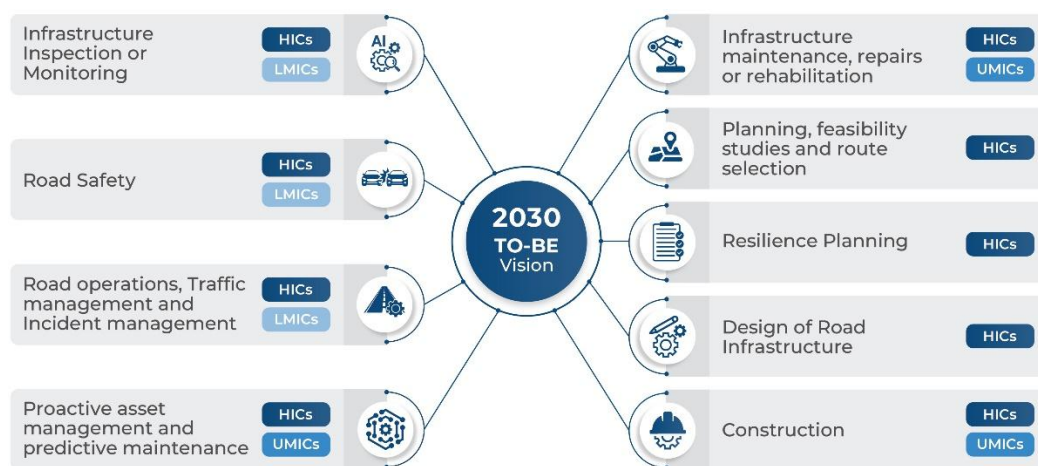


Figure 6.3: To-Be Vision for AI in the road sector in 2030.

6.2.1.1. HICs

In HICs, the overarching 2030 vision is for AI to become a key enabler of smart transport systems. Advanced ITS will use real-time AI analytics to manage traffic flow and reduce congestion on key routes with a large focus also expected in areas related to improving road safety. AI will be integrated with vehicles and smart traffic management systems, making roads and traffic more responsive to dynamic conditions. In 2030, HICs will likely have robust AI-based systems for predictive diagnostics, allowing authorities to better identify areas of road wear and tear which can help prevent accidents and reduce the requirement for major repair works by repairing damaged infrastructure before failures occur. Emerging capabilities such as AI-driven generative design for infrastructure and advanced DTs will enable real-time simulations and planning, greatly enhancing decision-making efficiency.

It is also expected that by 2030, AI-powered systems will be much more widely used for improving efficiency in managing infrastructure monitoring and maintenance, using ML algorithms to monitor bridges, tunnels, and roads. Large scale collection of asset information for road furniture (signs, safety barriers, road markings, studs, noise barriers etc.) is expected to be widely automated through the use of vehicle mounted cameras / LiDAR, with integrated AI algorithms for automated detection and classification of asset details. Similarly, pavement surface condition data is expected to be widely collected at a network level by many authorities, using vehicle-mounted equipment, or perhaps even satellite imagery. Although these methods cannot typically estimate the structural

characteristics of pavements, they can provide an overview of the road surface condition which can be used to support decision-making for asset management and maintenance strategies.

All of these techniques are already being used in many countries, but it is expected that they will be much more commonplace in HICs by 2030, and also will be adopted in many UMICs and even certain Lower MICs or LICs. In relation to inspection of bridges or tunnels, it is expected that progress will also be made in the adoption of drone-based, or vehicle-based measurements, combined with AI algorithms for identification of cracking or defects. However, given the safety-critical nature of the structural inspection process, it is expected that these technologies will gain increasing popularity for supplementing existing visual inspection processes, but will not completely replace them by 2030 until there is greater understanding of the limitations across the industry and until robust standards and guidelines are developed. Again, this technology is expected to be more commonly adopted in HICs and UMICs compared to Lower MICs or LICs.

AI-based methods for the early-stage planning, route selection and feasibility studies are expected to be much more developed by 2030, however the adoption of such methods is likely to vary depending on the requirements of local statutory procedures for individual countries, and whether AI-based methods can be aligned with these requirements. Given the importance of sustainability and environmental impact assessment in relation to the current climate crisis, it is also expected that AI will be utilised to provide more precise/automated methods for considering carbon and environmental impacts as part of the planning, design, and construction of road infrastructure. Additionally, AI will play a critical role in enhancing system resilience, enabling better preparation and response to extreme events and ensuring the continuity of transportation networks during disruptions. HICs are also expected to see continued integration of AI-based technologies during the design and construction stages, particularly in relation to improving site safety, reducing the time and cost of construction, and enhancing overall quality through automated construction and site inspection methods using robots, AR, and other similar technologies.

6.2.1.2. UMICs

The 2030 vision for UMICs involves focusing on cost-effective, scalable AI solutions. Given their developing infrastructure and financial limitations, these nations will prioritise AI tools that provide high impact with lower cost. For instance, AI-based traffic management systems will become more common, utilising video analytics and sensor-based technologies to manage road congestion and improve urban mobility. Additionally, targeting road safety applications, such as AI-powered tools for advanced driver warning systems and incident detection platforms, could help UMICs address road safety challenges effectively and affordably, drawing on similar approaches envisioned for LMICs.

By 2030, UMICs are expected to have implemented predictive maintenance systems to some extent, focusing on cost-efficient infrastructure monitoring solutions such as AI-driven deterioration modelling. In countries such as Mexico, the integration of sensors into roads and the use of AI to assess road surface conditions will help extend the lifespan of existing infrastructure while optimising repair budgets.

International collaborations and public-private partnerships will be crucial to achieving the 2030 vision in UMICs. These partnerships will help drive investment in AI infrastructure and transfer expertise from HICs, ensuring that UMICs are not left behind in AI adoption.

6.2.1.3. Lower MICs

Lower MICs, such as Tanzania and other developing nations, are currently in the early stages of AI adoption. By 2030, the vision for Lower MICs revolves around overcoming key infrastructural and financial barriers to utilise AI for road infrastructure improvements. While large-scale AI deployment may be limited by resource constraints, incremental AI integration, particularly in traffic management and road safety, will be within reach.

The vision for Lower MICs is to focus on targeted AI applications that yield immediate benefits at relatively low cost. For example, simple AI-powered tools for traffic monitoring, such as vehicle counting and speed detection, could be deployed in urban areas to reduce congestion and improve safety. AI applications for smart traffic lights that adjust to traffic conditions could also be introduced, providing cost-effective ways to manage urban mobility. Other tools for road safety, such as the data-fusion platform for incident detection and the camera-based technologies for advanced driver warning systems, presented in the case studies in this report, will also likely be further deployed across the various Lower MICs by 2030 as they represent relatively low-cost solutions with major potential road safety benefits.

AI is also expected to be used in data collection and infrastructure diagnostics, albeit at a smaller scale compared to HICs. This will help road authorities to better understand traffic patterns and maintenance needs, even with limited budgets.

6.2.1.4. LICs

LICs, such as Uganda and Mali, face significant challenges in implementing AI in the road sector, primarily due to limited infrastructure, lack of financial resources, and a shortage of skilled professionals. In 2030, the vision for LICs is to lay the groundwork for future AI adoption by investing in basic infrastructure development, upskilling professionals, and participating in international collaborations.

The vision for LICs is to focus on the development of AI-readiness strategies. These countries will need to prioritise investments in digital infrastructure, including reliable data collection systems and affordable access to IT resources. For example, Uganda has already indicated plans to benchmark its AI practices against international standards. By 2030, LICs will focus on building basic AI capabilities in areas such as traffic monitoring and maintenance planning. Additionally, solutions powered by emerging technologies like satellite-based AI tools and low-cost IoT sensors are expected to address infrastructural challenges unique to LICs. Partnerships with international AI organisations could introduce early access to modular AI innovations currently in development.

International aid and partnerships will be critical for LICs to realise their 2030 vision. Collaborations with international road agencies and private sector partners will help develop shared AI infrastructure, such as pooled data servers and cloud-based AI systems, reducing the cost of entry into AI-driven road management.

Furthermore, LICs will focus on capacity building, ensuring that professionals are trained in AI systems management. The goal by 2030 is to have a skilled workforce capable of handling basic AI applications, preparing the country for larger-scale AI implementation in the future.

6.2.2. Legislation and governance

6.2.2.1. HICs

From a regulatory standpoint, HICs will continue to lead efforts towards international harmonisation of AI standards. The regulatory landscape for AI in the road sector is evolving, with significant progress in HICs such as the EU AI Act, which categorises AI applications by risk levels. However, low- and middle-income countries face challenges due to underdeveloped frameworks. International organisations and collaborations are expected to bridge these gaps by promoting standardised guidelines that address ethical concerns, bias mitigation, and cybersecurity while supporting innovation. These efforts will align diverse regional strategies towards a cohesive global regulatory outlook.

By 2030, these nations will have developed or refined comprehensive regulatory frameworks for AI in the road sector, closely aligned with international standards such as the EU AI Act. To support this, NRAs should implement dynamic governance mechanisms that allow for iterative updates to policies as AI technologies evolve. Additionally, the creation of cross-border regulatory coalitions and advisory boards can ensure shared learning and harmonisation of AI standards globally.

These regulations will govern AI ethics, data privacy, bias reduction, and cybersecurity in AI-enabled infrastructure. More specifically, in the EU, the requirements for 'high-risk' AI systems will come into force in 2026, and by 2030 it is expected that the practical implications of these requirements for the transport sector will be better understood and NRAs, road operators and other organisations working in the road sector will be expected to have policies and procedures in place to comply with the requirements of the EU AI Act.

Moreover, HICs are expected to push forward global collaborations that align AI development and implementation across borders. Countries such as the U.S., Canada, and the UK are likely to spearhead global efforts to unify AI standards for road management, including active involvement in international standards development through organisations such as ISO, SAE, and IEEE. These efforts will not only aim to establish robust global frameworks but also extend to include the perspectives and needs of low- and middle-income countries (LMICs), ensuring that standards are inclusive and applicable across diverse socioeconomic contexts. Facilitating participation from LMICs in these discussions will promote equitable access to AI advancements and support global harmonisation in AI-driven infrastructure management.

6.2.2.2. UMICs

UMICs, such as Mexico, Costa Rica, and Argentina, have demonstrated increasing interest in AI for road infrastructure. By 2030, these countries will aim to bridge the gap between their current nascent AI initiatives and the advanced implementations seen in HICs, however it is not expected that a similar level of legislative development will exist compared to HICs.

One of the major priorities expected for UMICs will be building a robust regulatory framework for AI in road infrastructure. While some nations have already started outlining AI-related policies, the goal by 2030 will be to implement comprehensive governance frameworks. These will focus on ensuring that AI adoption aligns with international best practices and considers data privacy, bias in AI systems, and the societal impacts of technology.

6.2.2.3. Lower MICs

In 2030, Lower MICs will likely have taken some steps towards developing basic AI frameworks that support these smaller-scale applications, focusing on building internal expertise and capacity to manage AI systems.

However, the regulatory environment will continue to lag behind HICs and UMICs unless external assistance is mobilised and it is expected that many of the AI deployments seen in these countries will not be stringently regulated. In 2030, Lower MICs are expected to be developing foundational AI policies, modelled on successful frameworks from other regions. International organisations, such as the United Nations and World Bank, will play a critical role in providing technical assistance, capacity-building programmes, and financial support to these nations.

6.2.2.4. LICs

Similar to Lower MICs, regulatory frameworks, policy and governance specifically surrounding AI in LICs are expected to remain largely under-developed by 2030, meaning that any AI deployments in LICs by 2030 will likely not follow any specific rules or regulations. However, awareness of international developments in AI, and the relevant regulatory frameworks, is likely to extend to LICs who will be in a position to prepare for future deployments by starting the development of relevant policy which will ultimately lead to regulation of AI in the longer-term and will benefit from lessons learned in other countries where AI deployment has advanced at a quicker pace.

6.3. OPPORTUNITIES ASSOCIATED WITH AI IMPLEMENTATION

Based on the findings of the literature review, surveys, interviews and case studies, a number of potential opportunities or benefits associated with the adoption in the road sector were identified. These opportunities and benefits are summarized in Figure 6.4, and discussed under the subsequent headings. For each opportunity or benefit, a short discussion on recommendations for increasing the likelihood of that benefit being achieved is included.

 Opportunities and Benefits	Operational Benefits to NRAs / Road Operators	Societal Benefits
Enhanced Road Safety	●	●
Enhanced Efficiency / Time Savings	●	
Cost Savings	●	
Improved Asset Management & Maintenance	●	
Improved Worker Safety	●	●
Improved Quality of Service	●	●
Improved Resilience Planning	●	●
Reputational Benefits	●	
New Job Opportunities & Evolving Roles	●	●

Figure 6.4: Key opportunities and benefits of AI in the road sector.

There are significant opportunities for AI implementation in the road sector. HICs, which are more advanced in their AI strategies, provide valuable models for other nations to emulate. For instance, the Czech Republic stresses the importance of reliable and detailed data for ITS and predictive diagnostics, offering a clear example of how AI can enhance road infrastructure. Similarly, the U.S. is exploring ways to harmonise AI implementation with international partners, recognising the potential for international collaborations to standardise AI approaches across borders.

There is also growing recognition of the role AI can play in improving road safety, maintenance, and traffic management. Costa Rica, for example, suggests using AI to manage traffic volumes in real time and detect deterioration in road surfaces. Meanwhile, Ireland points to opportunities for AI in bridge inspection using drone photo data banks, highlighting how AI could revolutionise infrastructure monitoring. The integration of AI in predictive diagnostics, traffic management, and maintenance could yield substantial cost savings, improved safety, and optimised resource allocation across the road sector. These opportunities align with broader goals of smart infrastructure development and ITS that many countries, especially high-income ones, are actively pursuing.

6.3.1. Enhanced road safety

As highlighted in many of the case studies presented in this report, the introduction of AI technology in the road improvements, along with improvements associated with the physical infrastructure and its impact on road safety. As reported by Transport for NSW, through camera-based enforcement, they have significantly reduced the level of mobile phone use while driving and have also been able to target drivers not wearing seatbelts. In Peru, Lima Expressa have reported notable improvements in their incident response times through the implementation of the data-fusion and AI powered 'Lanternn' software system for incident detection. The iRASTE project in India demonstrated how in-vehicle driver assistance systems, powered by AI, led to significant

improvements in the number of incidents, demonstrating a 40% reduction in collisions. They also showed how the collection of incident data, and near-miss data, also enabled high-risk areas to be identified and remediation measures implemented to the infrastructure to help avoid future collisions. The various technologies which focused on collecting infrastructure condition data, also indirectly influence road safety by facilitating better asset-management decision-making and overall providing safer infrastructure.



Recommendations:



In order to achieve road safety benefits, NRAs or road operators should focus on identifying the problems which they are trying to address. For example, incident response, infrastructure condition, and driver-behaviour are 3 separate areas, which can all lead to improvements in road safety, with each area requiring different AI-based technologies to provide benefits. An important first step in improving road safety should be the collection and leveraging of road safety data.

In many HICs this is already carried out as part of daily operations, however, in LICs, LowerMICs and UpperMICs which do not already collect robust incident data sets, this represents a first step in the process. Data strategies should focus on how to collect and leverage statistics on incidents, using AI, or other processes. Effective public engagement was also observed to be an important influencing factor on the success of many of these safety-related AI systems, along with ongoing and targeted training and education of those engaging directly with the systems.

6.3.2. Enhanced efficiency / time savings

One of the key emerging benefits which was observed from the introduction of AI-based technologies in the road sector, was the ability to carry out tasks much more quickly, and often more accurately, than when carried out directly by a human. It was reported that in Brazil, the application of AI-based technology to automatically analyse and categories features recorded in video footage, demonstrated that automation of this approach allowed manual operatives to work 56 times faster. As an added benefit, the results were found to be more accurate when using the AI-based approach as it reduced the level of human error which was inherent in the extremely labour-intensive approach of manually reviewing video footage of the road network. Lima Expressa noted that their control room operators were able to work much more efficiently while also being able to identify and respond to many road traffic incidents which they would not have otherwise known about. In general, all of the technologies focused on collection and classification of infrastructure condition monitoring demonstrated significant improvements in the time taken to carry out surveys, often enabling much wider and more extensive data collection than was possible using more laborious traditional inspection methods. Overall, the majority of AI-based technologies presented in this report demonstrated some level of improvements in efficiency or time-related savings, which was often a key objective of implementing AI.

**Recommendations:**

For LICs and LowerMICs, a key recommendation would be to focus on technologies which can provide a quick and impactful return on investment. Learning from existing case studies to identify solutions which may provide enhanced efficiencies at a reasonable cost will help to build support. It is noted that for certain technologies, the upfront costs may be expensive, and benefits may not be immediate. HICs and LMICs should focus on establishing strong business cases which consider the whole-life cycle benefits of implementing AI technologies.

For example, in Denmark, it was noted that the initial planning and implementation of specialised drone flight paths for bridge inspection resulted in costs which were greater than a traditional visual inspection, however for subsequent inspections these costs will no longer exist, and the inspection process will be much quicker and more streamlined.

6.3.3. Financial cost savings

In most cases, improved efficiencies resulting from AI-based technologies can translate directly into financial cost savings. Some examples show how integration of BIM and AR/VR technology can provide significant cost savings on construction sites to avoid costly construction errors. Improved methods for rapid collection and classification of infrastructure assets and their condition, eliminate extensive costs associated with traditional inspection or survey methods, meaning that they are typically much more cost-effective solutions. The data collected from these systems also enable better decision-making with regard to proactive maintenance and asset management which also has financial benefits in the longer term when considering the overall life cycle of road infrastructure. Proactive maintenance interventions tend to favour small preventative interventions at regular intervals to avoid reaching a stage where major expensive repairs to infrastructure are required. In general, as demonstrated throughout this report, most AI solutions which focus on improved efficiency of tasks, also result in cost savings.

**Recommendations:**

A general recommendation for NRAs or road operators is to ensure that business cases focus on whole life costs, rather than just examining the immediate up-front costs of the technology. Some technologies will have a longer return on investment duration than others, and costs may appear prohibitive unless examined considering longer-term investment strategies. From an operational perspective, education and training is recommended as a key strategy to ensure that the technology is utilised properly and that the efficiencies and associated cost savings are achieved.

6.3.4. Improved asset management and maintenance

One of the primary objectives of implementing AI-based technologies in the road sector, to-date, has been focused on more widespread, quicker and more accurate collection of information about infrastructure assets and their condition (bridges, pavements, signs, road markings etc.). This information is primarily used as an input for asset management decision-making, which is used to inform ongoing maintenance strategies. The ability to collect more information about the location, type and condition of different assets will have significant benefits for asset management, allowing

much more holistic and accurate deterioration modelling and enabling better decision-making. Although the case studies presented in this report do not focus, in extensive detail, on the specific benefits achieved through better asset management, this will become an increasingly growing area where benefits will be achieved.



Recommendations:



NRAs and road operators should focus on leveraging the additional asset data which can be collected to ensure that it can effectively feed into the asset management decision-making process. In many cases, it may be beneficial to integrate AI-based infrastructure survey data into asset management systems. Benefits can also be achieved through the introduction of AI-based asset management systems which use ML and AI technology to carry out life-cycle assessments based on different potential maintenance regimes to optimise maintenance strategies.

A key difference between HICs and countries within the different LMIC categories likely lies in the current level of development of their inspection and asset management processes. In HICs, the main benefit will likely be related to enabling proactive decision-making, however in LICs, it is likely that in many cases, there is very little systemically collected infrastructure condition data. In such countries, the AI benefits are likely to be more relevant to enabling collection of general data around the type of infrastructure, where it is located and whether there may or may not be issues affecting the functionality of the road.

6.3.5. Improved worker safety

For many AI technologies there can be a positive impact on worker safety. In many HICs we have already seen AI being used on construction sites for improved health and safety. This can include the use of AI-powered robots, drones, or machines to carry out inspections or activities which would be dangerous for humans (e.g. inspections in confined spaces, or excavations). For general inspection and condition monitoring of road infrastructure, AI-based technologies can, in many cases, remove many of the dangerous activities associated with these inspections. Using traditional approaches, individuals often have to work at height, or on steep slopes adjacent to water or live traffic. Using automated and AI-based approaches to collect asset condition data can eliminate many of these risks.



Recommendations:



While AI technologies may not address all of the risks associated with construction, inspection and maintenance activities, there are some clear cases where there are direct safety benefits. It is advised to identify key areas of risk or concern and examine if AI-based technologies could be used to eliminate or mitigate these risks and to learn from industry reports or existing case studies to develop safety-related business cases for such technologies.

6.3.6. Improved quality of service

Most NRAs and road operators focus on providing a good quality of service to road users. This typically includes measures around journey times, delays, congestion and availability of roads amongst others. AI-based technologies can be used to directly improve quality of service, by improving signalling and traffic management and reducing congestion or delays on the network.

There are also many indirect benefits to the quality of service such as reducing incidents and the associated traffic delays or providing messaging/information to road users through ITS equipment such as variable message signs, or in-vehicle messaging. Similarly, improvements to infrastructure condition and safety also have indirect benefits on the quality of service, by providing more reliable infrastructure. In many cases in LICs, these improvements may provide access to essential healthcare services that would otherwise not be accessible to large parts of the community.

**Recommendations:**

While there are no specific recommendations related to adoption of specific technologies for improving the quality of service, it should be acknowledged in business cases for all technology implementation, that improved quality of service can be a direct or indirect benefit.

6.3.7. Improved resilience planning

Similar to the asset management benefits, there are also significant benefits for NRAs and road operators in their ability to understand and assess the resilience of their networks when they are subject to extreme scenarios such as extreme weather events or natural disasters. This is becoming increasingly pertinent given the climate crisis and the impact that increased frequency and intensity weather events are having on infrastructure networks. The ability to collect more widespread and more accurate infrastructure data allows better modelling and assessment of network-level resilience. Many frameworks and assessment methodologies already exist for resilience risk assessment for road networks; however, these methods are often limited by the availability of sufficient input data which will become increasingly available as AI-based solutions facilitate better data collection. In addition to the infrastructure data, additional data will also become increasingly available from crowd-sourced information (e.g. floating vehicle data) during normal road operations and during extreme events. This will allow better understanding of response strategies and their effectiveness and will provide additional training data for AI-based solutions which focus on modelling and assessing the resilience of the network.

**Recommendations:**

NRAs and road operators are encouraged to explore how additional data collected by new AI and other technologies can be leveraged to improve resilience planning and incorporate strengthening measures into asset-management decision-making. A focus should be placed on weather-related events which are occurring more frequently, and how expertise in weather modelling can be combined with infrastructure data to more accurately assess and plan road network resilience.

6.3.8. Reputational benefits

Very often when examining the activities of NRAs or road operators, there is a focus placed on the risk associated with reputational damage. However, there are also potential benefits in this regard by introducing new technologies and being seen to be at the forefront of technological development. This can be beneficial from a general public perception, but also amongst other road

operators globally, or for private companies looking to work in regions where they feel that their technological solutions will get buy-in and will be able to deliver benefits. Lima Expresa noted the general public perception around their introduction of AI to provide a better service to road users, and also by being recognised for their adoption of cutting-edge technology as an active intervention to address road safety challenges. Similarly, Transport for NSW noted that strong public support for their camera-based enforcement of mobile phone and seatbelt offences amongst drivers.



Recommendations:



While it is difficult to make specific recommendations for delivering reputational benefits, the case studies have demonstrated that appropriate public awareness and publicity campaigns can help with getting general public support for the adoption of AI. It should be noted that any such campaigns should be cognisant of the general local perception and should only be used where deemed appropriate or necessary.

6.3.9. New job opportunities and evolving roles

While fear of job replacement was a consistently highlighted concern, and often a cause of lack of engagement amongst the workforce. The case studies also highlight that when appropriate training, awareness and education is provided, workers generally embrace the technology and also are excited to explore the possibilities of their evolving roles where AI can be used as a tool to enable them to carry out their role more effectively. In many cases, there will also be requirements for new roles and personnel to manage new contracts, to provide AI-related expertise and to carry out new activities which were previously not possible without AI technology (e.g. effective enforcement of mobile phone and seatbelt offences).



Recommendations:



NRAs and road operators implementing a new technology should focus on identifying the key changes to existing roles which are likely to exist and should proactively engage with staff to reduce concerns around job replacement and focus on the opportunities associated with evolving roles. Separately, there should be a strong focus on the identification of new key roles which are required to effectively deliver new AI-based technologies to ensure that they can be resourced and the various benefits associated with the technology can actually be achieved. Education and training strategies should be defined to ensure that all of these areas are addressed accordingly.

6.4. CHALLENGES AND BARRIERS FOR AI IMPLEMENTATION

Based on the findings of the literature review, surveys, interviews and case studies, a number of key challenges or barriers which are likely to be faced during AI implementation in the road sector were identified. These challenges are summarised in Figure 6.5, and individually discussed under the subsequent headings. For each challenge, a short discussion on recommendations or solutions for overcoming the challenge is included.

AI implementation in the road sector faces several challenges that are exacerbated by differences in income levels, technological maturity, and regulatory preparedness. In LICs and Lower MICs, challenges include insufficient infrastructure, lack of skilled personnel, and limited financial

resources. These nations face particular difficulties in ensuring that AI technologies are compatible with existing infrastructure, which is often outdated or lacks the necessary digital capabilities to support AI systems. However, it is important to note that even in HICs, substantial outdated infrastructure lacking digital capabilities can present similar challenges. While these difficulties are particularly relevant in LICs and Lower MICs, they are also relevant for UMICs and HICs. Additionally, the high cost of AI technologies - ranging from software to sensors - poses a financial barrier.

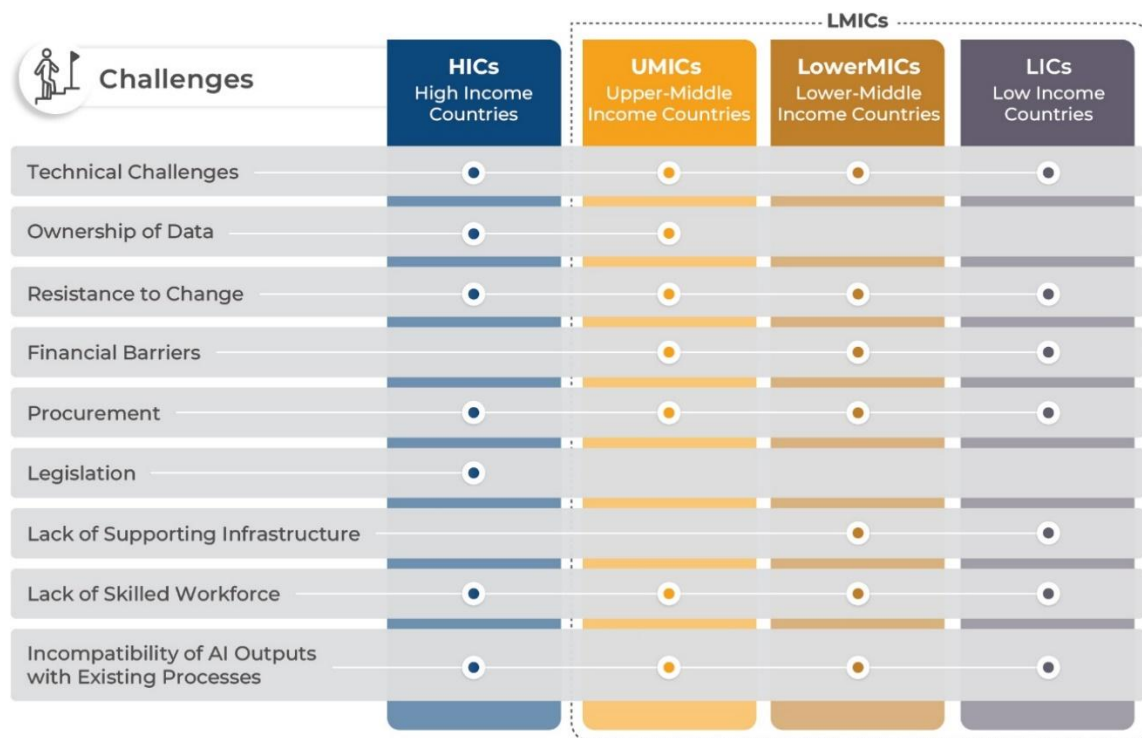


Figure 6.5: Key challenges and barriers for AI adoption in the road sector.

For example, Uganda recognises the need for investment in AI infrastructure but highlights the importance of cost-effective solutions that align with the financial realities of LICs. Similarly, Mali has raised concerns about the lack of access to powerful servers and IT infrastructure, which are critical for effective AI implementation. Despite these perceived barriers, the case studies highlight how AI technology are still being adopted in Lower MICs without the requirement for a great deal of expensive equipment or high-tech infrastructure.

On the regulatory side, uncertainty surrounding the legislative environment for AI technologies is a recurring issue. The survey indicates that 43% of respondents were unsure whether there is relevant AI legislation, while 76% expressed uncertainty about the future AI adoption-related regulations. This uncertainty complicates efforts to integrate AI in the road sector, especially in countries that lack the regulatory oversight to guide responsible AI use. In nations such as Argentina, future legislation is planned but currently undeveloped, signalling that the regulatory framework is still catching up with technological advancements. The use of particular computer vision technologies has raised privacy concerns relating to the personal data that has been collected. These technologies must comply with existing data protection laws by anonymising personal data. However, there are instances where data may not be anonymised, such as for payment purposes or enforcement of traffic violations. An example of this is AI technologies that

would monitor the interior of cars to detect distracted driving and their requirements to blur the faces of those that are monitored.

Another key aspect which was highlighted in various interviews with stakeholders that have implemented AI technologies is the requirement for education and training. Change in procedures for workers can lead to a reluctance to adapting to new processes which results in a delay and reduction in effectiveness of its implementation. Training is particularly important at the beginning of the implementation however, consistent technical training is also necessary to ensure the efficiency of the technology is maintained as many technologies will continue to evolve and develop. The interviews also highlighted the reluctance of workers to fully engage with the technology due to their perceived risk or concern that AI technologies would eliminate the value of their expertise or skills. This was particularly relevant for applications which would automate some of manual or labour-intensive processes such as road defect detection. To combat these challenges organisations provided suitable training for workers to ensure they had the knowledge and awareness to recognise that these technologies are tools that would make much better value of their skills and expertise.

A greater acceptance and engagement with AI technologies was observed once this training was conducted and this resulted in greater efficiencies for the systems. Another important aspect of training is to prevent overreliance on AI systems. Operators must be prepared to complete tasks manually in case of system malfunctions to ensure continuity and reliability in operations.

Another critical issue is the fragmentation of data governance frameworks across jurisdictions, particularly in Lower MICs where regulatory mechanisms are underdeveloped. Differences in governance structures can hinder cross-border collaborations and result in uneven access to AI innovations. Addressing this requires globally aligned standards for data security and algorithmic governance, with particular emphasis on interoperability and ethical considerations in AI design and implementation.

As AI increasingly shapes road management, traffic control, predictive maintenance, and infrastructure, it raises complex technical, ethical, and operational issues. These challenges are further complicated by the varied capacities of HICs to LICs, each encountering distinct obstacles to AI adoption. This section addresses key risks of AI in the road sector and identifies principal barriers to achieving the 2030 vision.

6.4.1. Technical challenges

The adoption of any new technology will inevitably introduce technical challenges which must be managed or addressed during the implementation process. This is no different with AI-based technologies. Findings from the literature review, surveys and interviews have demonstrated that technical issues can be varied in nature and complexity. The list below provides some examples of different technical challenges which can be experienced when integrating new AI-based technologies into the various activities carried out by NRAs or Roads Operators:

- Lack of computational power
- Calibration of AI-software based on local / domain-specific knowledge
- Technical integration with existing software or systems
- Software specific technical challenges
- Gaps in data collection when using AI for infrastructure condition monitoring

6.4.1.1. Lack of computational power

Lack of computational power was noted as a technical challenge in several countries; however, it was generally less of a concern in HICs. In LICs this was often a major obstacle, given that many AI technologies require data-intensive models to be run.



Solutions / recommendations:



A temporary solution which was adopted in certain LICs was to leverage the computational power provided by International Financial Institutions, such as World Bank, or the Inter-American Development Bank. This allowed them to run the models remotely and to gain the benefits of AI. Partnerships / collaborations with these types of organisations, or other organisations in HICs which can provide access to computing resources may represent a solution to this challenge in the short term, to enable AI to be leveraged in LICs. However, as AI-based technologies start to be deployed on a wider scale across LICs, this may no longer represent an appropriate solution. This may be offset by technological improvements in computational power, making solutions more affordable in the future.

6.4.1.2. Calibration of AI-software based on local / domain-specific knowledge

Another recurring challenge encountered across the majority of AI applications in the road sector related to calibration of AI-software based on local / domain-specific knowledge. One example of this was seen in Lima, where the AI-based data-fusion software generates alerts to help operators identify and manage incidents. The software was used on two different roads, which were distinctly different in nature and in how they were operated. On one road, the presence of pedestrians on the road was very common and was not of particular interest to operators, however on the other road, much more akin to a typical highway, the presence of pedestrians on the road represented a significant risk. Therefore, specific alert criteria (e.g. pedestrian on the road, animals on the road) had to be defined and calibrated separately for each road. This required input from the team with local experience and knowledge of the road operation. This calibration period took time, but was essential to ensuring that the software provided valuable alerts and insights.



Solutions / recommendations:



This challenge was successfully overcome in each case study included in this report, however it is important to highlight the fact that in each case, domain-specific expertise was an essential requirement to overcoming the challenge of calibration. Generally, this expertise also needs to be coupled with a good level of understanding of the AI technology, which means that experts in key areas of NRA/road operator activities, also need to develop understanding and expertise of AI-based solutions.

6.4.1.3. Technical integration with existing software or systems

Technical integration with existing software or systems is another challenge that is likely to occur as part of AI adoption. For example, when using AI to automatically monitor and classify the condition of pavements or bridges, there will often be a requirement to integrate the measured data into existing asset management systems. Similarly, AI-based solutions will likely require integration with other existing software systems for traffic management or operations.

**Solutions / recommendations:**

Similar to the challenge of calibration, this can be overcome with appropriate input from IT experts on existing systems. This often requires collaborative working between various parties or organisations to ensure a seamless integration process and to limit delays, data loss, or discontinuity of normal service.

6.4.1.4. Software-specific challenges

Software-specific challenges (or hardware challenges) are also experienced regularly, and are generally unique to the specific software, or the specific application of that software.

**Solutions / recommendations:**

Generally, software-specific challenges can be rectified through expertise from the providers of AI software solutions. However, well-developed contractual requirements can facilitate the provision of ongoing support and maintenance from providers to ensure that specific challenges can be rectified as they arise.

6.4.1.5. Gaps in data collection when using AI for infrastructure condition monitoring

Gaps in data collection when using AI for infrastructure condition monitoring can be experienced, and are often caused by limitations in accuracy or capabilities of AI-based solutions for capture and categorisation of infrastructure data. For example, in Oslo, when using the EyeVi solution to scan the surrounding infrastructure, classify pavement condition and identify different assets, there were certain areas where parked cars blocked the view of kerb lines or drainage assets. These areas had to be re-visited so that more data could be collected.

**Solutions / recommendations:**

The development of suitable processes, procedures and requirements for quality assurance and checking of data can provide a mechanism for minimising data loss or gaps in the data. Suitably designed contractual requirements can also help to minimise instances of avoidable data loss. However, it is noted that these processes and requirements will usually be specific to the technology and the application for which it is used, meaning that domain-specific expertise, coupled with knowledge of the AI technology, will typically be required to develop appropriate processes and fair contractual requirements.

6.4.2. Ownership of data

An emerging challenge that is highlighted by the ever-growing presence of AI technologies relates to uncertainties around ownership of data. Examples of this can be in cases where AI-based solutions utilise multiple data feeds from various sources (e.g. systems which ingest TomTom or Google Traffic Data, along with data from ITS equipment on the road network and weather forecast

data etc.), or in scenarios where AI systems generate data about the condition of the network, which is retained by 3rd party service providers. In many countries, these types of services are outsourced to service providers, consultants or contractors who provide services to road operators. It can often be infeasible for road operators to store or retain the data which is being generated internally, or even to manage it, depending on the resources available. This challenge already exists, to some extent, particularly in HICs. However, as significant quantities of new data become available through the adoption of AI technologies, this may pose significant additional challenges.



Solutions / recommendations:



At a high-level, NRAs or road operators should define data strategies which govern, at an organisational level, their philosophy on collection, generation, procurement and management of data. Specific challenges and risks associated with individual use cases can be mitigated by having well written contractual arrangements and through strong collaboration/involvement with organisations who understand the processes of the NRA/road operator.

6.4.3. Resistance to change

A widespread challenge faced during the adoption of AI technologies in the road sector is the resistance to change among individuals. This occurs for a multitude of reasons, which are generally as a result of people not fully understanding the technology or its role. Fear of job replacement is often cited as a source of such resistance. While AI technologies certainly can provide efficiencies, sometimes automating tasks previously carried out by humans, in most cases, AI serves as a tool to assist people in carrying out their tasks more efficiently and effectively. Lack of trust in the technology was also a regular theme when examining the reasons for such resistance, where individuals, often with extensive experience in performing specialist roles, were apprehensive about the reliability and accuracy of the outputs from AI-based solutions. A broader source of resistance stemmed from people's inherent reluctance to alter work processes, procedures, or embrace new technologies they did not fully understand.

**Solutions / recommendations:**

In almost all cases examined in detail as part of this study, the resistance to change primarily stemmed from a fundamental lack of understanding of AI and its role. This is usually overcome through educating and upskilling of the workforce and also people in leadership or decision-making roles. Training and educational awareness programmes should focus on a few key areas. One key aspect of training relates to specific technical training in the AI system to provide users with a comprehensive understanding of how it works. Separate to this, there should be a focus on teaching users about the benefits of AI, and how it fits into their day-to-day tasks, and in many cases will change the nature of their role, without eliminating it.

Another key aspect of training, or general awareness, comes in the form of educating those in leadership roles or in direct management positions. Training should aim to address concerns from staff or organizations resistant to AI adoption, enabling them to effectively engage and alleviate these apprehensions. If there are cases where job replacement may result from improved efficiency or automation, there should be strategies to ensure that people are given opportunities to upskill or transition into different roles which can provide added value. In many cases, it was necessary to provide ongoing training at regular intervals to keep staff engaged and to ensure that the maximum benefits were being achieved. In some cases, positive incentives or reward schemes were shown to work well to increase staff engagement with technology.

6.4.4. Financial barriers

Some of the main benefits associated with using AI are related to improved efficiency, and reduced costs. However, in many cases, upfront costs can be prohibitive for the roll out of a new technology, and in some cases, the cost savings are not immediate. In some cases, the business case for collection of infrastructure condition data to facilitate better asset management, will not see a return on investment for many years. To make it even more challenging, a significant advantage of having improved asset management, lies in the ability to carry out pro-active maintenance interventions to target at-risk infrastructure, before it has any effect on the functionality of the road network. However, in many countries where maintenance budgets are limited, infrastructure owners and operators can often only justify reactive maintenance measures when trying to manage large networks with significant quantities of assets which may require attention. In HICs, financial barriers for adoption of new technologies tend not to be a major challenge, as long as an appropriate business case can be developed to justify costs. However, in many LICs, financial barriers represent a significant challenge for the adoption of many AI-based technologies. For example, the cost of satellite imagery was noted as a barrier for the solution proposed by TRL for classification of dirt roads. This led to a cost-effectiveness assessment being undertaken to identify the best trade-off between image resolution (i.e. cost) and accuracy of outputs from the AI classification algorithms. Similarly, simple things like buying a camera to mount on a vehicle to collect video footage was not always straightforward in some LICs.



Solutions / recommendations:



The key recommendations for this challenge are aimed at LICs and LowerMICs. Partnerships with Development Banks and International Financial Institutions should be leveraged to generate funding for outline pilot studies or trials. These trials should be designed so that upon conclusion, the findings can be used to demonstrate the benefits associated with the use of AI. The results of such trials should also be used to feed into business cases, to lobby for funding of AI technologies, and where possible demonstrate cost savings, or other benefits, which can be achieved through funding of such initiatives.

Another recommendation is to focus on developing a cultural shift from 'reactive' to 'proactive' interventions. It can be difficult to justify, or explain, the benefits of investing in maintenance interventions for infrastructure which is not causing an immediate issue to the functionality of the road, however when considering a whole-life assessment of road infrastructure, it is well documented that cost savings can be significant when small interventions are carried out before major remediation is required.

6.4.5. Procurement

AI adoption in the road sector is still in its infancy and most deployments so far have been on a trial or pilot basis, meaning that procurement-related challenges have not been to the forefront. However, it is evident that the penetration of AI-based technology in the road sector is increasing at a rapid rate. Given vastly different nature of services required for supply and support for AI-based technologies, compared to traditional construction-based services required by road operators, this may pose challenges in ensuring that appropriate procurement approaches and contracts are used to ensure high-quality service provision. This will also be influenced by the general approach which NRAs or road operators take for AI adoption. Organisations may choose to outsource all AI-related services or may prefer to take an approach where they develop in-house expertise or systems. For countries falling within the LMIC categories, there may be a different range of procurement-related challenges. For example, it was noted that processes for procurement of satellite imagery, which was required for AI-based road classification in different African countries, were not well understood and proved to be challenging. The knowledge of partner organisations with previous experience in procurement of satellite imagery was leveraged to assist in the procurement process.



Solutions / recommendations:



Procurement approaches for new AI-based technologies will in many cases be software based. In HICs, NRAs or road operators will likely see themselves moving towards existing procurement models which are more suited to the provision of software as a service, or procurement of data-related services, rather than construction or works related contracts.

However, legal input to contractual agreements should be sought to ensure that requirements are aligned with the needs of the different activities carried out within the road sector. In countries falling within the LMIC categories, where procurement-related challenges arise, input from International Financial Institutions or partner organisations with expertise in procurement of specific hardware / software should be sought.

6.4.6. Legislation

Legislation is discussed at length in various sections within this report. Although AI-specific legislation is not yet widely developed on a global level, there are emerging legislative requirements governing AI use. Aside from data privacy laws, which are already well developed and well understood in many countries, the legislative landscape specifically for AI technologies is not yet well defined and the impact of such requirements on the road sector, are not well understood. This creates uncertainty in HICs, where legislation has already been developed, but is not yet well understood in practice. For example, The EU AI Act was enacted in 2024, however, requirements for 'high-risk' applications - which includes aspects of road operations – are expected to be enforced by 2026. At present, there are no clear definitions or guidance for AI systems or activities in the road sector will actually be governed by these requirements. In countries where AI legislation for the road sector is not yet developed, which includes the majority of countries in the LMIC categories, there are likely to be less legislation-related challenges in the short to medium term.



Solutions / recommendations:



The key recommendations for HICs, or any countries where AI-specific legislation is developing, are focused around developing an understanding of the legislation and creating national / organisation-specific policies around AI use, which align with governing legislation. Given the high-level of uncertainty which currently exists around legislative requirements, it is suggested that NRAs, or other bodies responsible for the management and operation of roads, should actively engage with working groups that are focused on pre-empting how legislation will impact practice.

For example, in Europe, the TM 2.0 working group is pre-emptively defining typical traffic management activities, and outlining their interpretation of which activities are expected to be 'high-risk' or otherwise, and hence subject to different requirements under the EU AI Act. For countries without any immediate emerging legislation governing AI use in the road sector, it is recommended to engage with countries which are further along the development path, and learn from best practice and challenges faced elsewhere, before developing their own AI policies.

6.4.7. Lack of supporting infrastructure

Physical and digital infrastructure is a necessity for large-scale AI adoption. This supporting infrastructure can include anything from processing power on an individual computer, to large-scale communications networks or data centres for transfer or storage of data. In HICs and many UMICs, hardware is typically readily available and accessible, and communications networks tend to be well-developed, however, in Lower MICs and LICs, in particular, the lack of supporting infrastructure is often a significant challenge in allowing the benefits associated with AI to be realised.

**Solutions / recommendations:**

As a short-term solution, LowerMICs and LICs should engage with International Financial Institutions, such as World Bank, or the Inter-American Development Bank, or other partner organizations who can provide access to computing power through cloud-based solutions. This will enable pilots to be progressed, which will show the potential benefits of adopting AI solutions and can potentially be used to lobby for funding of incremental improvements in supporting infrastructure.

6.4.8. Lack of skilled workforce

One key challenge which is repeatedly cited as a barrier for AI implementation is the lack of skilled workers. Although AI technologies can be used to automate many processes and introduce efficiencies, there is still a strong reliance on skilled workers. This includes individuals with AI-specific expertise, but also skilled workers with domain-specific knowledge in the road sector, who in many cases will need to upskill to allow AI technologies to be embraced. Although, this challenge is currently being faced in most countries globally, it represents a significantly greater and different challenge within the LMIC countries, in particular LICs. In these countries, limited numbers of well-educated or skilled people, suitable for technology-based roles, exist in the workforce, even outside of AI-specific expertise. Where skilled workers are available, they typically take on roles with significant levels of responsibility and are not available to solely focus on specific areas such as AI adoption.

**Solutions / recommendations:**

The general recommendation is for education and training, to allow workforces to be upskilled, however for LICs, this alone may not be enough. Skilled workers tend to migrate to regions with greater economic prosperity, or areas with more opportunities to utilise their skills.

As such, in the short to medium term LICs should leverage the expertise available to them through Development Banks and International Financial Institutions, international consultancies or multi-national organisations, who are working in their countries. Developing long-term relationships with these organisations to allow the AI industry to grow, will eventually lead to the development of further roles and opportunities and may help to attract and retain local skilled workers.

6.4.9. Incompatibility of AI outputs with existing processes

One important challenge which must be addressed relates to the fact that very often, the outputs from an AI-based technology will be different to the information or decision-making criteria which underpin existing processes and procedures for various activities carried out by NRAs or road operators. For example, in many countries, bridge condition monitoring typically relies on visual inspection by trained engineers who assess the condition of each element in the bridge and assign a dimensionless condition score to the bridge. Using AI-based technologies to automatically collect information about bridge condition means that the quantity of information will often be significantly greater, and more detailed, than what is traditionally recorded. Very often, the outputs

will therefore not be compatible with the existing approach and efforts need to be made to ensure that the outputs are appropriately aligned with the needs for infrastructure owners or operators.



Solutions / recommendations:



There are a few aspects which need to be addressed in this regard to ensure that maximum value is obtained from new technologies. First of all, local domain-specific expertise is required, during the initial integration stages, to ensure that the AI systems are providing useful and comprehensible outputs. In addition to this, consideration needs to be given to any additional useful outputs or information provided by AI systems, and how these can be incorporated into processes and procedures.

Finally, standards, guidelines and general processes/procedures need to be updated to allow for new technologies, and new information to be used as part of NRA activities (e.g. modifying standards for bridge inspection to allow drone-based inspections).

6.5. RISKS ASSOCIATED WITH AI IMPLEMENTATION

Based on the findings of the literature review, surveys, interviews and case studies, a number of key risks associated with the deployment of AI in the road sector were identified. These risks are summarized in Figure 6.6, and discussed under the subsequent headings. For each risk, a short discussion on recommendations or solutions for addressing or mitigating the risk is also included. For Lower MICs and LICs, a key consideration is determining the necessity of pursuing advanced AI technologies versus investing in foundational infrastructure. While AI can offer long-term cost savings and efficiency, its immediate return on investment may be outweighed by the benefits of enhancing basic infrastructure. Detailed cost-benefit analyses should be conducted to evaluate whether AI solutions provide substantial advantages over traditional methods, especially in resource-constrained settings. This approach ensures that investments align with the socio-economic priorities of these countries.

In addition, thorough preparation is crucial when implementing AI projects in the road sector. A comprehensive and well-detailed feasibility study is essential to ensure that AI initiatives are viable and aligned with broader objectives. A strategic approach is required, with clearly defined goals, including environmental sustainability, traffic safety and long-term economic benefits. It is imperative to prevent investments from being self-serving or driven solely by political motivations, as AI projects can be costly and appealing for short-term gains. Instead, success should be measured by their genuine contribution to higher added value in the transport sector.

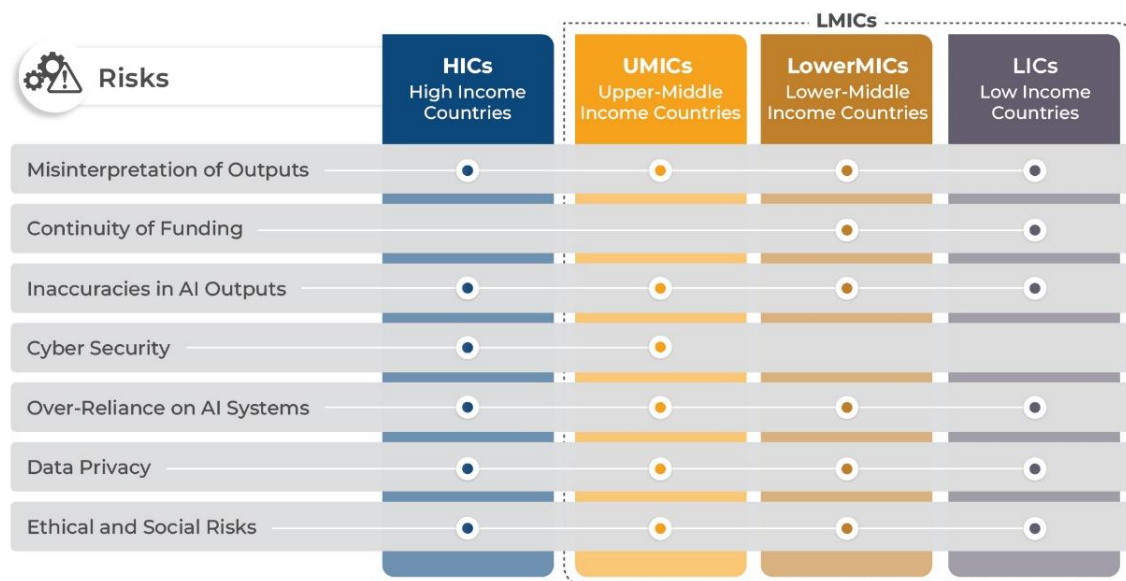


Figure 6.6: Key risks associated with AI adoption in the road sector.

6.5.1. Misinterpretation of outputs from AI systems

When introducing a new technology which provides outputs to assist with carrying out tasks or activities which are traditionally carried out by human operatives, there is a risk that the information is not understood or utilised in an appropriate manner. This introduces the possibility that the value of using AI systems may not be realised, if the outputs are not understood, or if incorrect decisions are made on the basis of misinterpretation of the information.



Solutions / recommendations:



The general recommendation is for education and training, to ensure that users of AI systems can understand the outputs and can also understand how they should be interpreted and used for decision-making. In addition to training and education, domain-specific expertise during the introduction of new AI technologies is also important to ensure that the outputs from any systems are aligned with the operational needs of NRAs or road operators, and that they are presented in a comprehensible and useful way.

6.5.2. Continuity of funding for AI technologies

This risk is a potential concern in LICs and Lower MICs, where lack of funding can be a challenge. In many countries within LIC and LowerMIC categories, funding availability and budgets for the road sector can vary significantly from year to year. Funding may be made available for initiatives such as AI deployment, from International Financial Institutions or even from government budget allocations. However, even if this funding is made available and allows pilots, trials, or even ongoing deployment of AI technology, there is a significant risk that this funding may not remain available in subsequent years, irrespective of the value that may be demonstrated. This also has the knock-on effect of lowering confidence in the effectiveness of any new technologies, because interruptions in funding streams reduces the chances of successfully demonstrating the potential benefits. Even in HICs the cost requirements for the project as a whole should be considered,

ensuring adequate funding for development, operation, and long-term maintenance throughout the entire lifecycle. This will help mitigate the risk of insufficient resources for sustaining the system beyond its initial implementation.



Solutions / recommendations:



There are no clear or obvious remedies to mitigate against this risk. However, as a short to medium term solution, collaborations with International Financial Institutions or other funding agencies for LICs or LowerMICs, should focus on implementing pilots which can demonstrate clear and quantifiable benefits to put forward a strong business case for ongoing funding by government bodies.

The recommendations in any business cases built upon these pilots, should emphasise the aspects which will require ongoing funding to ensure continuity of delivering benefits.

6.5.3. Inaccuracies in AI outputs

There are often significant concerns around the accuracy of outputs from AI models, which can lead to mistrust. Where systems are used for enforcement, as outlined in the case study for mobile phone use and seatbelt detection in New South Wales, it is imperative that the accuracy of the system can be ensured. The review carried out as part of this research has highlighted that there are various potential sources of error or inaccuracy in different AI systems, with some of these noted below:

- Misclassification of infrastructure features for inspection / monitoring
- Incorrect classification of infrastructure defects for automated inspection
- Incorrect incident alerts for traffic operations
- Gaps in data caused by technical issues
- Biased outputs due to biases in the underlying training datasets

The risk associated with inaccuracies is of course directly related to the use case. For AI systems which are being directly used for legal enforcement or for providing time sensitive incident response guidance, the outputs should be extremely accurate. However, for a system which provides predictive maintenance suggestions, there is a much lower risk. In general, the risk is usually linked to the level of human input in the decision-making process, and the stage in the process at which human interaction occurs.

**Solutions / recommendations:**

There are a number of ways in which this risk can be minimised or mitigated. Firstly, it is suggested that processes which utilise AI systems should include human-in-the loop checking/calibration. In addition to this, calibration of AI systems should incorporate tests and validation exercises to compare outputs against predefined acceptance criteria to ensure accuracy.

General education and training will also help in allowing staff to identify and react appropriately to errors in system outputs. In order to ensure accuracy and also to minimise issues related to errors or biases in the underlying training datasets, NRAs and road operators should develop robust processes and procedures for data collection, processing and storage, including QA and accuracy reporting of data along with identification of limitations/shortcomings and training of staff to recognise these.

6.5.4. Cyber security

Cyber security is already a major concern for infrastructure operators, whose networks have become increasingly vulnerable to cyber-attacks, as digitalisation of physical infrastructure becomes commonplace. Data breaches and hacks have been experienced by many infrastructure operators, who must invest significantly in digital security measures to mitigate this risk. The introduction of AI-based technologies into the road sector, means that additional data will quickly be generated and used, but also means that tasks which are automated through AI processes can also pose cyber security risks. The obvious high-risk item for roads relates to cyber-attacks for automated of vehicles, which fall outside the scope of this report, but nevertheless highlights the importance of addressing cyber security risks associated with AI implementation. Automated control of traffic signals, as an example, can have direct safety-related impacts if subject to a cyber-attack which alters signalling, which also leads to reputational damage for the road operator.

**Solutions / recommendations:**

The primary recommendation relates to the provision of appropriate cyber-security measures to protect AI-based systems from cyber-attacks. NRAs and road operators will already have various firewalls and solutions to mitigate some of these risks, however given the potential for increased risk with AI, there needs to be a greater focus on specific security measures for higher-risk AI applications.

The EU AI Act defines a risk assessment process, along with specific obligations for high-risk AI systems, and NRAs / road operators should develop robust processes and procedures for identify high-risk items and engaging with industry specialists to adopt the most appropriate security measures to minimise the risk of cyber-attacks.

6.5.5. Over-reliance on AI systems

Where staff become accustomed to using AI systems to perform tasks more efficiently and effectively, there is a risk that staff, process and procedures can become dependent on AI to carry out day to day tasks. For example, Lima Expresa in Peru, noted that their control room operators had fully embraced the Lanternn software system for identifying and managing incidents on their network. While this has resulted in significant operational benefits, the process for incident

detection and management is now significantly reliant on the system to assist the operators. In the case of a temporary crash or failure of the system, this can have significant negative impacts on carrying out business as usual given the growing dependence on the system. This has introduced a risk that did not exist prior to the introduction of the AI and data-fusion software, which now needs to be managed.

Additionally, the accuracy, clarity and reliability of the input data used by AI systems play a fundamental role in determining the effectiveness of automated decision-making. Poorly defined or unreliable data inputs can lead to flawed analyses, increasing operational vulnerabilities. Ensuring the proper definition of data scope, validation mechanisms, and continuous monitoring of data integrity is essential to maintaining the credibility of AI-assisted operations.



Solutions / recommendations:



NRAs and road operators should focus on developing appropriate contractual requirements or Service Level Agreements to ensure operational resilience on the system side. In addition to this, there should also be a focus on ensuring that processes incorporating AI-systems also include provisions for operating without AI systems in particular emergency scenarios where the system may not be available.

6.5.6. Data privacy

Data privacy represents a primary risk associated with any system which collects, stores or uses any information which is not intended for public consumption. Personal data about individuals, or sensitive details, poses a particular risk if not appropriately collected and stored. In many countries there are strict laws around how personal data is collected, how it is used, how it is stored and how it is made secure. In addition to personal data, other examples of datasets which NRAs and road operators collect include information about the condition of their assets which is generally used for internal asset management decision-making, or incident logs with sensitive details about the nature of collisions or other traffic incidents on the network. Most of this information is used for internal operations and not intended to be shared with 3rd parties. With the introduction of AI systems, there will be a significant increase in the level of data which can be collected and utilised, as these systems typically rely on large datasets to train underlying ML algorithms. Technologies such as facial recognition and automatic number plate recognition mean that personal/sensitive data can quickly be collected on a large scale and if not managed appropriately, put NRAs or road operators at risk of breaching data privacy laws, or at greater risk if they fall victim to a cyber-attack.

**Solutions / recommendations:**

NRAs and road operators in most countries already have procedures and processes for managing data in a safe and secure way, particularly in many HICs where stringent regulations exist. However, it is important to recognise the increased risk which AI systems can introduce and to ensure that contractual requirements are robust in relation to compliance with data protection laws, and also with regard to cyber security. Providers of AI systems should be asked to demonstrate their processes for collecting, deleting, anonymising and securely storing/transferring data.

Where public facing AI systems are being used, such as camera-based enforcement, the risk associated with public concerns over data privacy should be addressed, where appropriate, through specific media campaigns to demonstrate processes for collecting, deleting, anonymising and securely storing/transferring data to ensure transparency around these procedures. The requirement for public media campaigns will be dependent on the local perception towards AI technologies and data privacy concerns, so will only be appropriate in certain circumstances.

6.5.7. Ethical and social risks

The ethical implications of AI deployment in road infrastructure must be carefully considered. AI systems inherently carry biases from their training data, which may affect decision-making and lead to inequitable outcomes. For instance, if AI algorithms are predominantly trained on data from urban areas, they may prioritise urban infrastructure over rural regions, potentially reinforcing existing disparities in access to quality road infrastructure. This is particularly relevant for Lower MICs and LICs, where rural populations may already face limited access to road services. In addition, the reliance on automated decision-making raises concerns about transparency and accountability. Without clear regulatory frameworks to govern AI deployment, it can be difficult to identify responsible parties in case of system failure or unintended consequences, leading to public mistrust and hindering the adoption of these technologies. AI systems can inadvertently reinforce existing societal biases, including those related to gender and diversity, when trained on unrepresentative datasets. For instance, models developed without diverse data inputs may disproportionately prioritise certain groups' needs over others. This can manifest in road planning or maintenance decisions that inadvertently favour urban over rural settings, impacting women and marginalised groups who are often underrepresented in transport data.

**Solutions / recommendations:**

In order to ensure accuracy and also to minimise issues related to errors or biases in the underlying training datasets, NRAs and road operators should develop robust processes and procedures for data collection, processing and storage, including QA and accuracy reporting of data along with identification of limitations/shortcomings and training of staff to recognise these.

AI policies and procedures, along with data collection strategies, should consider suitable approaches which can reduce or eliminate potential biases from datasets and minimise ethical and social risks associated with AI.

7. RECOMMENDATIONS

Section highlights



An array of targeted recommendations for (i) road administrations, and (ii) PIARC, aimed at facilitating the effective implementation of AI in the road sector across different income country levels.



A detailed roadmap outlining the essential steps and milestones for achieving successful AI integration in road infrastructure by 2030, across different income country levels.

7.1. INTRODUCTION

This section outlines recommendations to help PIARC members transition from the “As-Is” scenario to the “To-Be” AI implementation in the road sector by 2030. The recommendations target NRAs, ROs, and service providers, with advice for PIARC. A strategic roadmap for the transition is included, with recommendations tailored to the needs of HICs, UMICs, Lower MICs, and LICs, summarised here and detailed in the report.

This chapter builds upon the key findings and recommendations presented in the previous chapter. While the preceding sections outlined the current challenges, risks, and opportunities associated with AI adoption in the road sector along with specific recommendations for addressing each, this chapter consolidates and expands on those insights, providing a high-level structured framework for implementation. Readers who may have skipped directly to this section are encouraged to refer to the previous chapter for a more in-depth understanding of the context underpinning these recommendations.

Many of the recommendations outlined here are aligned with or derived from the practical solutions discussed earlier in the report. For instance, the challenges identified in AI governance, workforce upskilling, and regulatory adaptation (detailed in Section 6) directly inform the universal principles outlined in Section 7.2. To ensure coherence, the recommendations presented in this section reinforce and expand upon the earlier analysis, offering actionable guidance for road administrations and PIARC members.

The universal principles for AI transition in the road sector (Section 7.2) are intended to address the broader strategic considerations identified in the previous chapter. These principles serve as a foundation for the more specific recommendations that follow. Given the increasing role of AI in infrastructure management, it is essential to emphasise that successful implementation requires a structured and phased approach, as discussed in the roadmap in Section 7.3.

7.2. UNIVERSAL PRINCIPLES FOR AI TRANSITION IN THE ROAD SECTOR

Before outlining roadmaps for HICs and LMICs, it is crucial to establish universal principles for effective AI integration in the road sector. These principles offer a strategic foundation for all NRAs, ensuring a structured and equitable approach to AI adoption by 2030.

1. **Governance and regulatory frameworks.** A strong governance structure is essential for AI adoption, with clear regulations, ethical guidelines, and cybersecurity protocols. NRAs must create transparent policies to address AI risks as outlined in Section 6.
2. **Capacity building and workforce development.** AI implementation requires investment in human capital. Road administrations should prioritise upskilling, offering training to ensure staff can operate, maintain, and optimise AI technologies.
3. **Data Infrastructure and digital preparedness.** Reliable AI systems require high-quality, standardised data. NRAs should enhance data collection, interoperability, and management to support accurate and efficient AI operations.
4. **Collaborative innovation.** International cooperation and private sector engagement are crucial for AI scalability. NRAs should build partnerships to leverage technology and funding.
5. **Inclusivity in AI deployment.** AI adoption must benefit all regions, including rural and underdeveloped areas. Equity-focused policies should prevent disparities in AI-driven road management.

7.3. ROADMAP: TRANSITION FROM THE “AS-IS” TO THE “TO-BE” VISION

The roadmap to achieving the 2030 vision for AI in the road sector should be tailored to countries' income levels, recognising their unique challenges and opportunities.

7.3.1. HICs

The diagram in Figure 7.1 outlines a roadmap for AI integration in infrastructure and transport for HICs, tracking its progression from 2024 to its projected large-scale adoption by 2030. It highlights key areas of AI implementation, strategic development pillars, and anticipated advancements.

In 2024, AI was already enhancing infrastructure monitoring and transport operations. Around 24% of applications focus on infrastructure inspection, improving asset management. 14% involve drone-based remote sensing, enhancing data collection and site assessments. Additionally, 48% of stakeholders use some form of AI in road operations, traffic management, and incident detection, contributing to road safety improvements. Observations from multiple countries confirm measurable safety benefits.

To enable large-scale AI adoption, four strategic pillars have been identified. Investment in pilot projects is essential to quantify benefits and establish viable business cases. Workforce education and training will enhance skills and awareness of AI capabilities. The development of AI-enabling systems and processes will support data accuracy and scalability. Finally, policy development is crucial for ethical deployment and regulatory compliance.

By 2030, HICs are envisaged to see AI playing a key role in infrastructure inspection, predictive maintenance, and autonomous transport systems. It will also aid early-stage project planning, route selection, and feasibility studies, while its use on construction sites will enhance safety, inspection, and operational efficiency.

7.3.2. UMICs

The corresponding diagram for UMICs is presented in Figure 7.2.

In 2024, AI is primarily being utilised in road operations, traffic management, and incident detection, demonstrating its growing role in enhancing transport efficiency and safety. Additionally, road safety is identified as a high-priority use case, reinforcing AI's potential to mitigate risks and improve traffic management systems.

Four strategic pillars have been identified. Investment in pilot projects and trials is essential to assess AI benefits and explore deployment opportunities. Enhancing public-private partnerships will promote knowledge transfer, fostering global benefits from AI-driven technology. The development of scalable AI solutions is critical to ensuring that AI systems can be deployed efficiently across entire road networks. Finally, the establishment of a regulatory framework is necessary to ensure the ethical and responsible development of AI technologies.

By 2030, UMICs are anticipated to have adopted video analytics and sensor-based technologies for congestion management, AI-driven infrastructure inspection, deterioration modelling, and predictive maintenance systems.

7.3.3. Lower MICs

A similar diagram for Lower MICs is presented in Figure 7.3.

In 2024, AI has already been trialled in asset management and infrastructure inspection, marking the initial phase of its adoption. Additionally, road safety is identified as a high-priority use case, reinforcing AI's potential to enhance safety measures and mitigate risks in transport networks.

Four key pillars have been established as shown in Figure 7.3. Prioritising low-cost AI applications will enable high-impact solutions targeting critical issues such as road safety and infrastructure degradation. Investment in digital infrastructure is essential to develop reliable data collection and storage systems that will support AI advancements. Seeking funding for collaborative trials through partnerships with international organisations will promote cooperative projects and accelerate AI deployment. Lastly, the development of a basic regulatory framework will establish foundational regulations for AI ethics, ensuring responsible and compliant implementation.

By 2030, Lower MICs are envisaged to have adopted low-cost traffic management systems, AI-driven infrastructure inspection, and road safety applications, including defect and 'blackspot' detection within road networks.

7.3.4. LICs

Figure 7.4 illustrates the progression of AI for LICs. In 2024, AI usage in LICs remains limited, while early-stage trials have been conducted for asset management and infrastructure inspection. These initial implementations are designed to assess AI's viability in improving infrastructure monitoring and management.

Four strategic pillars have been identified. Developing AI readiness strategies involves assessing infrastructure gaps and devising action plans. Focusing on foundational AI applications will prioritise solutions requiring minimal investment but offering immediate benefits, such as traffic monitoring applications. Capacity building and upskilling will enhance awareness of AI technologies, encouraging professionals to develop AI-related expertise. Finally, participation in international collaborations will provide access to technical support and infrastructure, including cloud-based AI systems, from global organisations.

By 2030, LICs are anticipated to have adopted reliable data collection systems, implemented AI-driven road infrastructure identification and classification, and adopted traffic monitoring and maintenance planning.

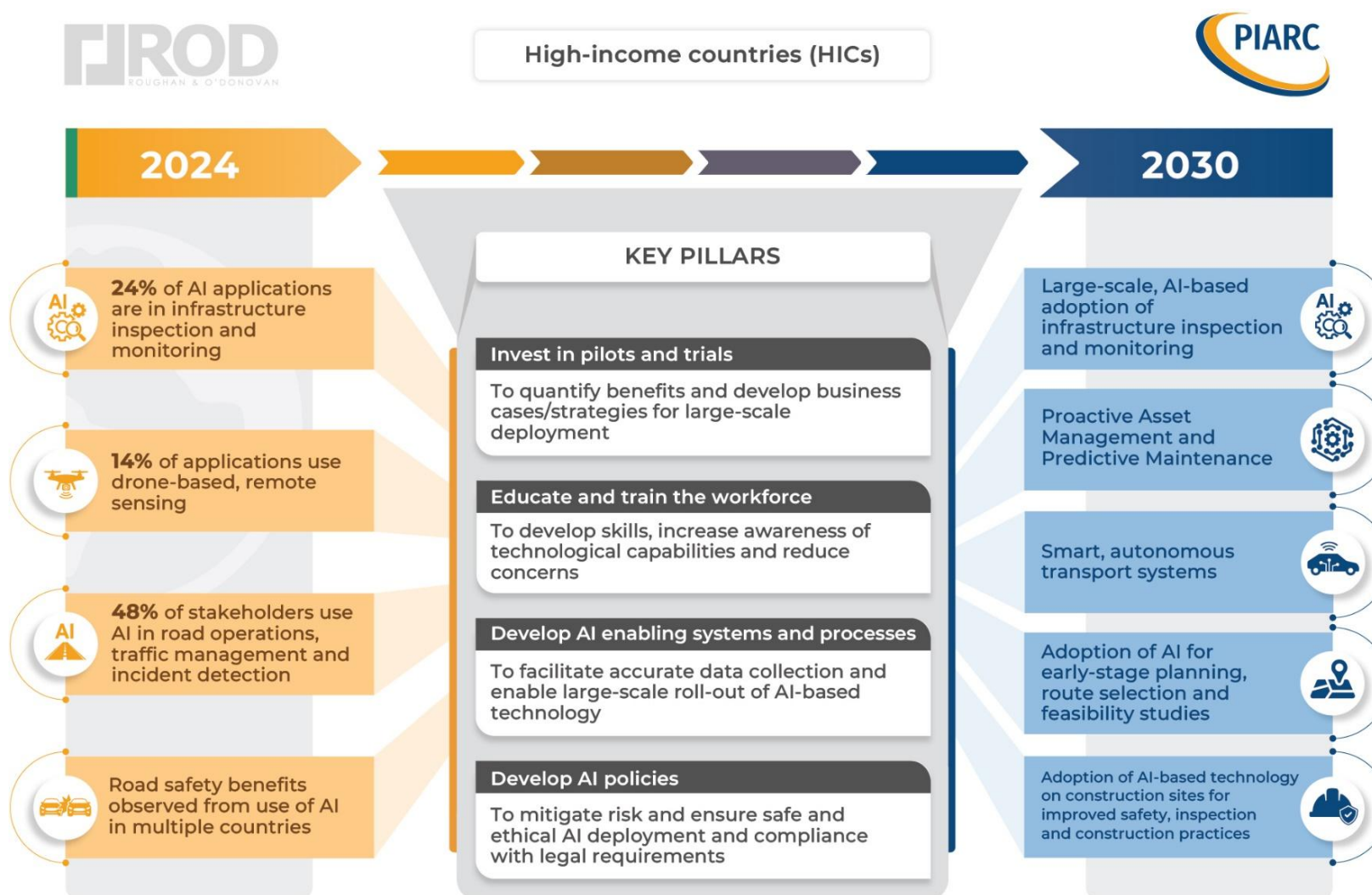


Figure 7.1: Roadmap for AI adoption in HICs.

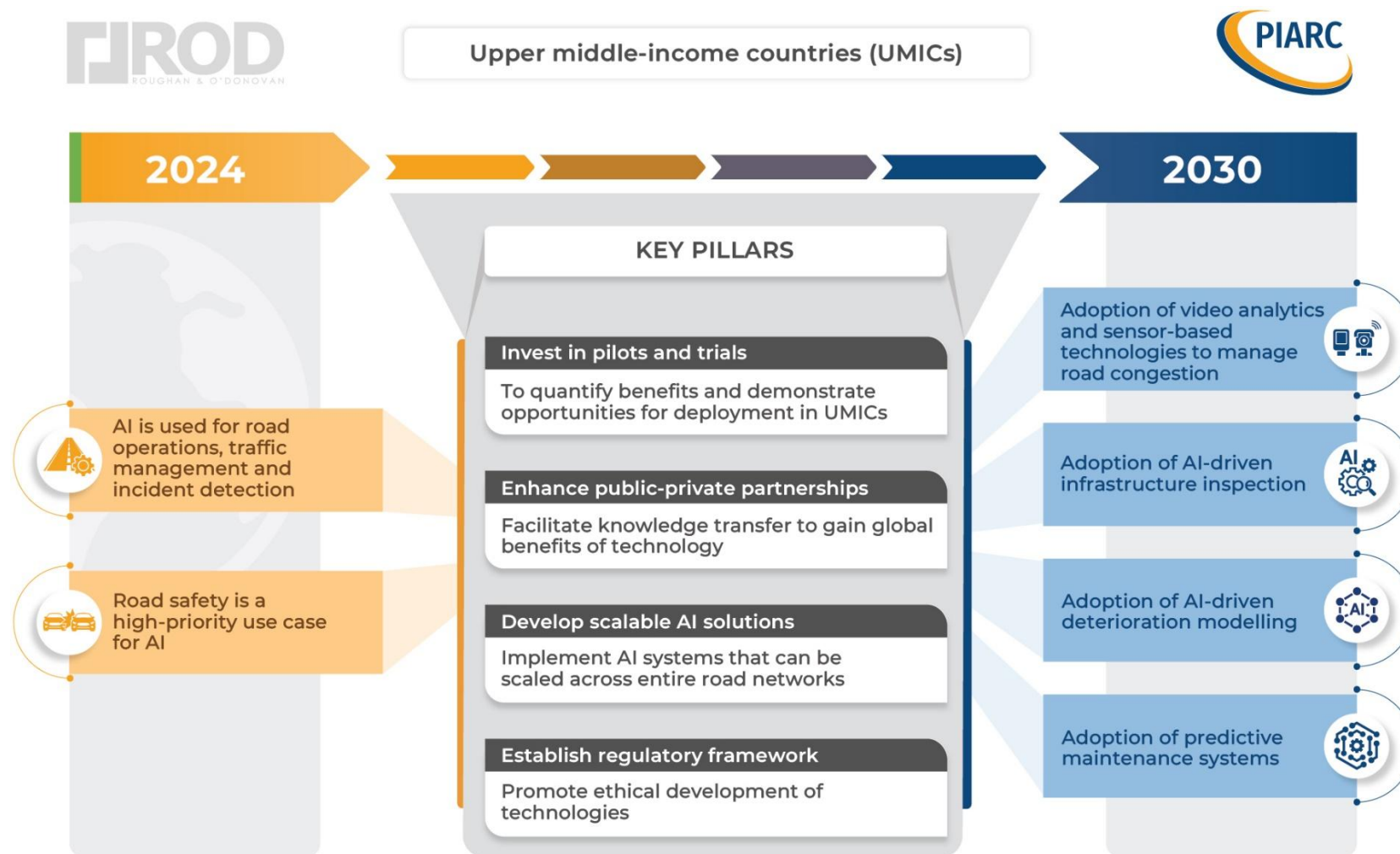


Figure 7.2: Roadmap for AI adoption in UMICs.

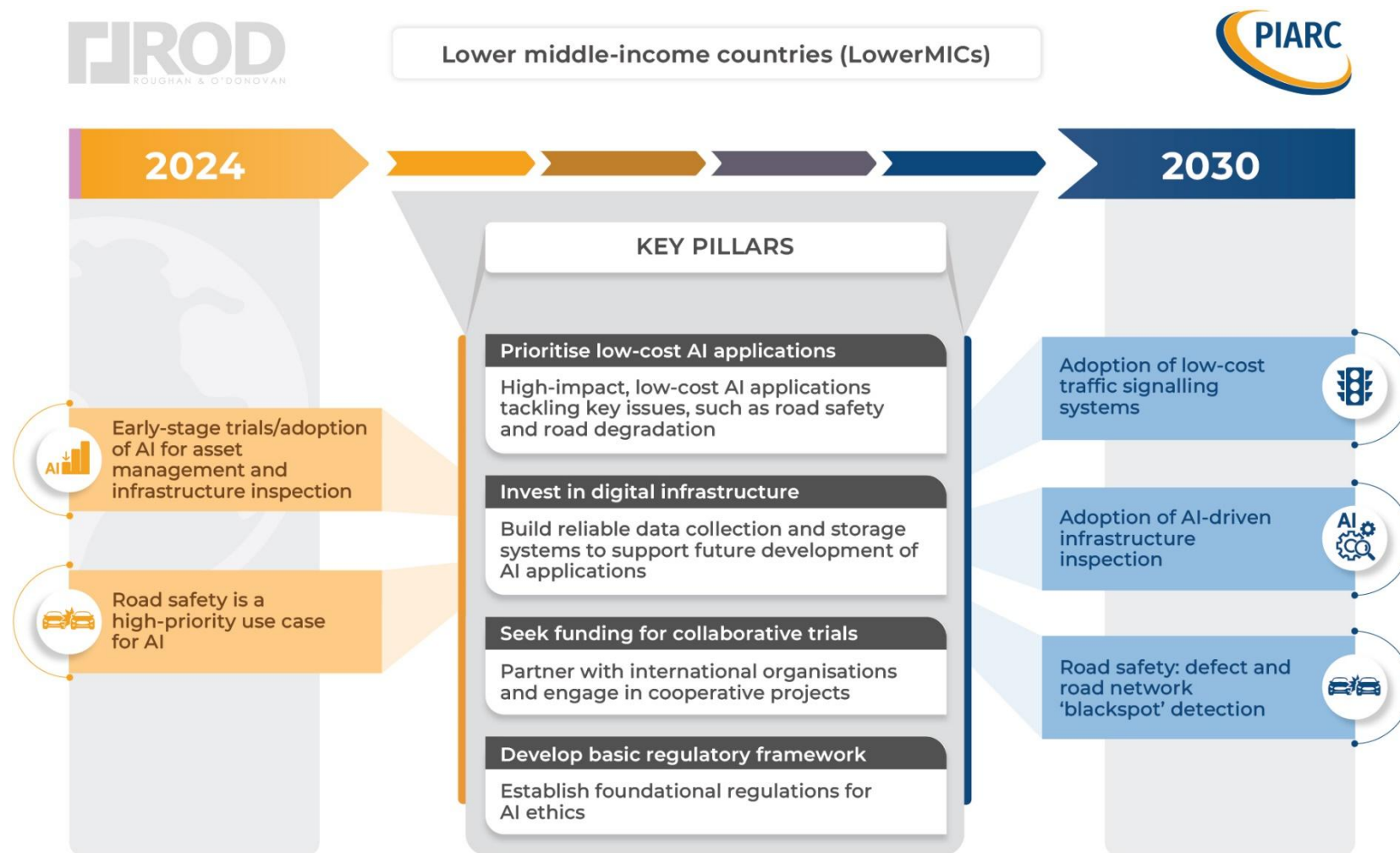


Figure 7.3: Roadmap for AI adoption in Lower MICs.

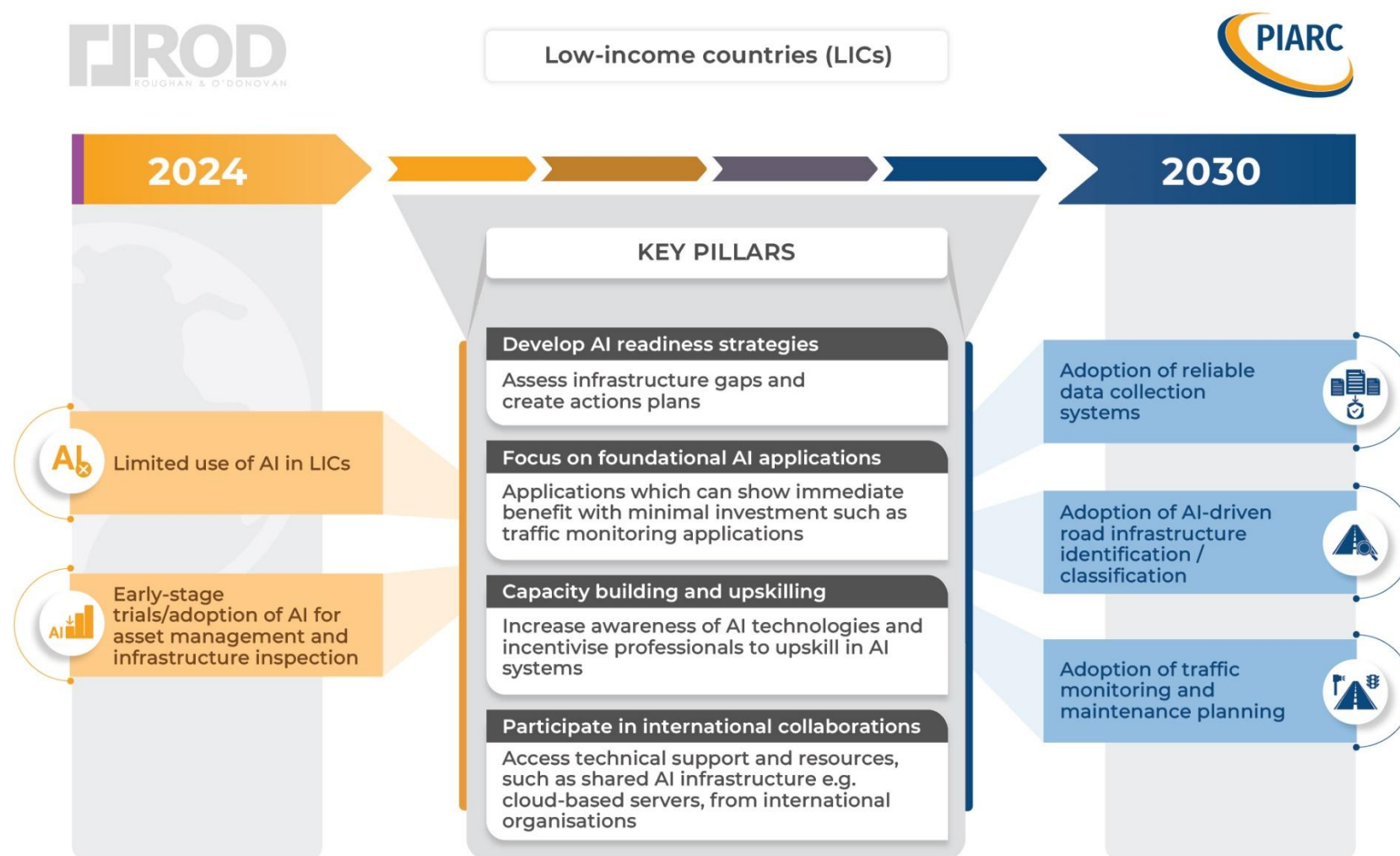


Figure 7.4: Roadmap for AI adoption in LICs.

7.4. RECOMMENDATIONS FOR ROAD ADMINISTRATIONS

In Section 6, challenge-specific individual recommendations were provided for overcoming each of the different challenges and risks, along with recommendations for maximising the likelihood of achieving each of the potential benefits and opportunities. This section provides a high-level summary of these recommendations.

Table 7.1 also visual summary of these recommendations, highlighting the key aspects which organisations from countries of different socio-economic development should focus on, to initiate the transition to AI in the road sector. It should be noted that many of the recommendations are relevant to all countries, however, the recommendations presented in this section focus on the key priority areas which should be addressed initially by countries in different socio-economic categories, to realise the 2030 vision for AI in the road sector.

7.4.1. General recommendations

1. **Establish robust regulatory frameworks:** To address ethical concerns and standardise AI implementation, regulatory frameworks must be established. HICs should focus on international harmonisation of AI standards, while LMICs should prioritise developing AI governance structures, supported by international bodies, to ensure contextually relevant and enforceable regulations. Key priorities include data privacy, bias reduction, and cybersecurity for ethical and secure AI deployment.

Road authorities should establish guidelines and regulations for the private sector to develop AI responsibly in the road sector, prioritising public interests, ethical standards, and public policy goals. These should address data privacy, fairness in decision-making, and bias mitigation, while fostering transparency and accountability. Collaboration with academia, industry, and civil society is essential to create inclusive and enforceable regulations.

2. **Enhance data infrastructure and cybersecurity measures:** A comprehensive data management strategy is crucial to mitigating operational risks, as data quality directly impacts AI effectiveness. Converting non-digital data into AI-compatible formats is a key challenge, especially in road-related fields. Road asset data should be acquired and organised for long-term, multi-purpose use. Investment in data infrastructure ensures AI models are trained on high-quality, representative data. In Lower MICs and LICs, collaboration between NRAs and private companies can pool data, reduce costs, and promote standardisation. Accurate location data, privacy protection, and strengthened cybersecurity protocols are essential to safeguard AI systems and maintain public trust.
3. **Promote inclusive and equitable AI deployment:** To mitigate social risks, AI deployment must be equitable, addressing urban and rural needs. Policymakers and developers should prioritise diverse data to ensure AI systems reflect populations' needs. In Lower MICs and LICs, focusing on basic AI applications in rural areas can enable broader integration while addressing infrastructure gaps.
4. **Strengthen capacity-building initiatives:** Capacity-building programs are crucial to bridging the skills gap, especially in Lower MICs and LICs. International organisations, e.g. the World Bank and United Nations, should fund and organise training to equip professionals with AI skills. Collaboration between HICs and LICs can foster knowledge transfer, strengthening global AI readiness.
5. **Training and upskilling of workforce:** To optimise AI systems, the workforce must be trained to understand the functionalities and capabilities of these systems. Once workers recognise the benefits and added-value which can complement their own skills, reluctance

to adopt new processes will decrease. Continuous training and upskilling as systems evolve is essential to maintain effectiveness.

6. **Technical collaboration:** Collaboration between AI/software providers and end users' operational expertise is key to success, whether technical or domain-specific, such as infrastructure or traffic conditions. Early-stage collaboration is vital for successful implementation.
7. **Revision of processes and procedures:** Given AI's focus on new data and decision-making, local or international guidelines may need updating to enable effective use. For example, inspection and asset management processes in many countries may require changes to accommodate new technologies and incorporate broader quantitative data for asset condition assessments.
8. **Consider a holistic approach:** The benefits of an AI system can extend beyond its direct purpose. For example, driver assist systems reduce collisions through improved behaviour, while collected data can aid in redesigning dangerous roads and addressing high-risk blackspots. AI systems should not be viewed in isolation, as they often need to be paired with public awareness or educational campaigns for maximum effectiveness.

7.4.2. HICs

HICs, with advanced infrastructure, financial capacity, and regulatory preparedness, are leading AI adoption in the road sector. AI usage is growing, hence, key recommendations focus on safe, ethical deployment, balancing safety and trust with efficiency. These steps will ensure continued leadership and AI integration:

1. **Accelerate the deployment of AI enabling systems and processes:** Road administrations in HICs should prioritise the integration of AI into smart, autonomous transport systems. Investments in AI-based traffic management and safety, predictive diagnostics, and maintenance tools, such as AI-driven deterioration detection and drone-assisted inspections, will be crucial for managing aging systems.
2. **Invest in pilots/trials:** HICs are encouraged to invest in AI trials to introduce efficiencies into business processes. Pilots/trials should be designed to demonstrate added value and to allow potential challenges of wider scale deployments to be identified and understood. It is also recommended to include measurable/quantifiable targets to support business cases for further deployments. The results, including case studies in this report, will help develop strategies for larger-scale deployments.
3. **Invest in education & awareness:** Deployment strategies should include upskilling and training of existing staff, recruitment of specialists when needed, and general education and awareness among staff and the public. This will help avoid or mitigate people-related barriers and challenges.
4. **Consider climate change and resilience planning:** HICs should consider how integration of AI-based technologies can be incorporated into the planning, route selection, and feasibility phases of new road projects, or ongoing operation and maintenance, with a view to reducing environmental impacts. Furthermore, resilience planning should include maintaining network continuity during and after extreme events, ensuring that road

infrastructure remains operational under adverse conditions such as floods, wildfires, or other climate-induced disruptions.

5. **Demonstrate added value:** The International Transport Forum (ITF) prepared a detailed report on 'AI in Proactive Road Infrastructure Safety Management.' This purpose of this paper was to highlight the road safety benefits of proactive rather than reactive road infrastructure safety management. The paper discusses various measures to increase acceptance and adoption of AI technologies for road authorities. One of these key measures was to predict the economic benefit associated with the implementation of the technology as this will act as an incentive for road authorities to adopt new technologies (ITF OECD, 2021).
6. **Understand the risks:** Develop risk assessment methodologies to evaluate AI deployment risks and mitigation strategies. Assess factors such as biases, errors, or incomplete datasets, and the consequences of inaccurate AI outputs.
7. **Develop AI policies:** Given advanced AI development in HICs, road administrations should create policies addressing challenges such as data privacy, AI ethics, bias, and cybersecurity, aligned with regulatory frameworks. They should also consider international standardisation, particularly with the EU AI Act and ISO regulations, to reduce uncertainty as global AI regulation evolves.
8. **Foster international collaboration:** HICs should lead global collaborations, partnering with LMICs to share expertise and best practices. This will help establish AI standards and ensure that developing countries are not left behind in AI adoption.
9. **Invest in AI research and innovation:** HICs should allocate resources to AI research in transport, focusing on technologies e.g. AI-powered predictive maintenance and smart traffic systems to improve mobility. Collaboration with academic institutions and tech developers will accelerate innovation.
10. **Gender Inclusion and Diversity:** HICs are encouraged to utilise AI systems that are free from inherent bias. Bias within datasets must be minimised or at least understood to prevent discriminatory outcomes. Organisations involved in AI research, development, deployment, and monitoring should actively promote gender-balanced and inclusive teams. Mandating diversity within AI teams can enhance representativeness, reduce algorithmic bias, and improve fairness in AI systems. Policymakers should consider guidelines or requirements to ensure equitable participation in AI-related decision-making, fostering a more inclusive and socially responsible AI ecosystem.

7.4.3. UMICs

UMICs, despite financial and infrastructural limitations, show interest in AI adoption. To progress, UMICs should focus on cost-effective AI solutions and regulatory development.

1. **Focus on pilots and trials:** To understand the benefits, costs, and challenges, UMICs should invest in AI trials. The results will identify risks and inform decisions on large-scale deployments.
2. **Develop scalable AI solutions:** UMIC road administrations should focus on scalable, low-cost AI applications with high impact. Prioritising AI-driven traffic management, predictive maintenance, and sensor-based infrastructure monitoring can extend infrastructure lifespan and optimise repair budgets.

3. **Invest in education & awareness:** Deployment strategies should include upskilling and training of staff, recruitment of specialists where needed, and education and awareness for staff and the public. This will help avoid or mitigate people-related barriers and challenges.
4. **Establish comprehensive regulatory frameworks:** UMICs must prioritise AI governance frameworks for road infrastructure, addressing data privacy, bias, and societal impacts, while aligning with international best practices.
5. **Capacity building:** UMICs must invest in capacity-building initiatives to train professionals in AI management, ensuring local expertise to maintain AI systems effectively.

7.4.4. Lower MICs

Lower MICs face adoption challenges due to infrastructure and financial constraints, but with targeted interventions, they can progress in AI integration and benefit from lessons learned elsewhere.

1. **Focus on low-cost AI applications:** Lower MICs should prioritise cost-effective AI solutions, such as AI-powered traffic monitoring, vehicle counting, speed detection, smart traffic lights, and road safety technologies. These can improve safety and traffic management while being financially accessible.
2. **Develop basic regulatory frameworks:** Road administrations should develop foundational AI regulations addressing ethical, legal, and societal considerations. These frameworks should align with international standards and be tailored to the needs and capabilities of Lower MICs.
3. **Utilise international technical assistance:** Lower MICs should engage with international organisations such as the World Bank, the United Nations, and PIARC to access technical assistance and financial support for AI infrastructure development.
4. **Identify opportunities for funding collaborative trials:** Lower MICs should also engage with international organisations to identify organisations or potential avenues for funding trials of AI-based technologies which may provide benefits at low cost.
5. **Invest in digital infrastructure:** Road administrations should prioritise investments in digital infrastructure, focusing on establishing reliable data collection systems, cloud-based AI systems, and sensor technology to support AI-driven road management.

7.4.5. LICs

LICs face challenges such as limited infrastructure, finances, and skilled personnel. To prepare for future AI adoption, the following steps are recommended.

1. **Develop AI-readiness strategies:** LICs should prioritise the development of AI-readiness strategies, focusing on building basic infrastructure, such as communications infrastructure, reliable data collection systems and affordable IT resources.
2. **Capacity building and upskilling:** LICs must invest heavily in capacity-building initiatives to upskill professionals in AI systems management. Collaborations with international institutions will be key to providing training and technical expertise.

3. **Participate in international collaborations:** Road administrations should engage in international collaborations to pool resources, such as shared AI infrastructure (e.g., cloud-based servers), and access technical support from global AI experts.
4. **Focus on foundational AI applications:** LICs should start with simple AI applications, such as traffic monitoring, road safety solutions, and basic predictive maintenance tools, which can offer immediate benefits with minimal investment.
5. **Improve technological awareness:** By focusing on key pilot projects and detailing their benefits it can influence leaders to have a change in culture in respect to AI. This will promote further adoption of AI technologies.

Table 7.1: Summary of key recommendations and primary focus areas for transition to AI in the road sector.

 Recommendations	LMICs			
	HICs	UMICs	LowerMICs	LICs
Accelerate the deployment of AI enabling systems and processes	●			
Invest in pilots/trials	●	●		
Invest in education & awareness	●			
Consider climate change and resilience planning	●			
Demonstrate added value	●			
Understand the risks	●			
Develop AI policies	●	●	●	●
Foster international collaboration	●			
Invest in AI research and innovation	●			
Gender Inclusion and Diversity	●			
Develop scalable AI solutions		●	●	
Capacity building		●	●	●
Establish comprehensive regulatory frameworks		●	●	
Focus on low-cost AI applications			●	●
Utilise international technical assistance			●	●
Identify opportunities for funding collaborative trials			●	●
Invest in digital infrastructure			●	●
Develop AI-readiness strategies				●
Participate in international collaborations				●
Focus on foundational AI applications				●
Improve technological awareness				●

7.5. RECOMMENDATIONS TO PIARC

PIARC, as a global body for road infrastructure, has a key role in facilitating AI adoption across countries of varying income levels. The following recommendations will help PIARC support global AI integration:

1. **Promote international standards for AI:** PIARC should lead efforts to harmonise AI regulations and standards across countries, facilitating global collaboration and ensuring consistent AI implementation practices. Encouraging the adoption of international AI standards, such as ISO certifications, will ensure interoperability and safety across borders.

2. **Support capacity-building initiatives:** PIARC should facilitate training programmes and workshops that target professionals in LMICs, helping these countries build the necessary skills to manage and maintain AI systems. PIARC can also foster knowledge-sharing platforms where countries can exchange best practices and experiences in AI adoption.
3. **Facilitate international collaborations:** PIARC should play a key role in fostering collaborations between HICs and LMICs to transfer expertise, knowledge, and technologies. These partnerships will help address the technical and financial barriers faced by LMICs in AI adoption.
4. **Provide technical assistance:** PIARC should offer technical assistance to countries that lack the expertise to develop and implement AI strategies. By collaborating with global technology experts and road authorities, PIARC can help LMICs develop tailored AI-readiness plans.
5. **Develop an AI working group:** Given the focus on AI in the road sector, its potential benefits, and the uncertainty around evolving legal frameworks, PIARC could consider two approaches. One option is to form a dedicated Technical Committee for AI integration in the road sector. Another is to incorporate AI into existing committees, embedding expertise within areas such as infrastructure maintenance, road safety, and traffic management. A hybrid approach, combining both options, may also be considered. PIARC should evaluate the best method based on its goals and resources.

8. GLOSSARY

Term	Definition
ADAS	Advanced Driver Assistance Systems
AI	Artificial Intelligence
ANPR	Automated Number Plate Recognition
AR	Augmented Reality
AV	Automated Vehicle
BAC	Blood Alcohol Concentration
CCTV	Closed-Circuit Television
CNN	Convolutional Neural Network
CVI	COWI Virtual Inspection
DMS	Driver Monitoring System
DT	Digital Twin
EIA	Environmental Impact Assessment
eMOS	enhancing Motorway Operation Services
EU	European Union
GDPR	General Data Protection Regulation
GIS	Geographical Information System
GNSS	Global Navigation Satellite System
HICs	High-Income Countries
IAPP	International Association of Privacy Professionals
IFI	Independent Fiscal Institution
IoT	Internet of Things
iRAP	International Road Assessment Programme
ITS	Intelligent Transport Systems
KPI	Key Performance Indicator
LICs	Low-Income Countries
LiDAR	Light Detection and Ranging
LLMs	Large Language Models
LMICs	Low & Middle Income Countries
LowerMICs	Lower-Middle-Income Countries
LRA	Local Road Authority

Term	Definition
ML	Machine Learning
MPDC	Mobile Phone Detection Camera
MR	Mixed Reality
NIMS	Network Intelligence & Management System
NIST	National Institute of Standards and Technology
NLP	Natural Language Processing
NN	Neural Network
NRAs	National Roads Authorities
PIARC	World Road Association
POT	Project Oversight Team
RCM	Reality Capture Model
RF	Radio Frequency
ROD	Roughan & O'Donovan
ROI	Return of Investments
ROs	Road Operators
RTK	Real-time kinematic positioning
SaaS	Software as a Service
SHM	Structural Health Monitoring
SLA	Service Level Agreement
TRL	Transport Research Laboratory
UAV	Unmanned Air Vehicle
UMICs	Upper-Middle-Income Countries
VR	Virtual Reality

9. REFERENCES

- [1] Access Partnership (2024), Brazil's New AI Bill: A Comprehensive Framework for Ethical and Responsible Use of AI Systems, Available at: <https://accesspartnership.com/access-alert-brazils-new-ai-bill-a-comprehensive-framework-for-ethical-and-responsible-use-of-ai-systems/>
- [2] Acusensus (2024) Technology description, Available at: <https://www.acusensus.com/solutions/headsup>
- [3] AI Training Act (2024), US AI Training Act, Available at: <https://www.congress.gov/bill/117th-congress/senate-bill/2551>
- [4] Anachkova M. et al. (2021) Design of low-cost wireless noise monitoring sensor unit based on IoT concept, Journal of Vibroengineering, 23(4), pp. 1056–1064, <https://doi.org/10.21595/jve.2021.21709>
- [5] Anagnostopoulos C. (2006) A License Plate-Recognition Algorithm for ITS Applications, IEEE Transactions on ITS, 7(3), pp. 377-392, Available at: <https://doi.org/10.1109/TITS.2006.880641>
- [6] Asad et al. (2022) Pothole Detection Using Deep Learning: A Real-Time and AI-on-the-Edge Perspective, Advances in Civil Engineering, article id 9221211, pp. 1-13, Available at: <https://doi.org/10.1155/2022/9221211>
- [7] Arrieta-Rodríguez E. et al. (2019) Prototype for identification of vehicle plates and character, IOP Conf. Series: Materials Science and Engineering 519, 012028, Available at: <https://doi.org/10.1088/1757-899X/519/1/012028>
- [8] Argyroudis S. et al. (2024) Digital technologies can enhance climate resilience of critical infrastructure, Climate Risk Management, 35, 100387, Available at: <https://doi.org/10.1016/j.crm.2021.100387>
- [9] Aimsun (2024) Technology description, Available at: <https://www.aimsun.com/aimsun-insight/>
- [10] Attentive (2024) Technology description, Available at: <https://attentive.ai/blog/property-measurement-software-for-estimating-snow-removal-jobs-attentive>
- [11] Australian Government (2024) Australia's Interim Response to Safe and responsible AI in Australia, Available at: https://storage.googleapis.com/converlens-au-industry/industry/p/prj2452c8e24d7a400c72429/public_assets/safe-and-responsible-ai-in-australia-governments-interim-response.pdf
- [12] Autodesk Generative Design (2024) Technology description, Available at: <https://blogs.autodesk.com/advanced-manufacturing/2017/11/15/autodesk-expands-autodesk-generative-design-tech-preview/>
- [13] Autodesk Generative Design (2024) Technology description, Available at: <https://blogs.autodesk.com/advanced-manufacturing/2017/11/15/autodesk-expands-autodesk-generative-design-tech-preview/>

- [14] Azam S. et al. (2016) Automatic license plate detection in hazardous condition, Journal of Visual Communication and Image Representation, 36, pp. 172-186, Available at: <https://doi.org/10.1016/j.jvcir.2016.01.015>
- [15] Bálint et al. (2022) Deep Reinforcement Learning based approach for Traffic Signal Control, Transportation Research Procedia, 62, pp. 278-285, Available at: <https://doi.org/10.1016/j.trpro.2022.02.035>
- [16] Bendris B. et al. (2022) Design and Experimental Evaluation of an Aerial Solution for Visual Inspection of Tunnel-like Infrastructures, Remote Sensing, 14(1), 195, Available at: <https://doi.org/10.3390/rs14010195>
- [17] Bentley GenerativeComponents (2024) Technology description, Available at: https://bentleysystems.service-now.com/community?id=kb_article_view&sysparm_article=KB0097624
- [18] Bentley OpenRoads (2024) Technology description, Available at: <https://www.cttec.ae/openroads/>
- [19] Bernardi M. et al. (2021) On the Use of Interferometric Synthetic Aperture Radar Data for Monitoring and Forecasting Natural Hazards, Mathematical Geosciences, 53, pp. 1781-1812, Available at: <https://doi.org/10.1007/s11004-021-09948-8>
- [20] Blin R. et al. (2019), Road scenes analysis in adverse weather conditions by polarization-encoded images and adapted deep learning, IEEE ITS Conference (ITSC), pp. 27-32, Available at: <https://doi.org/10.1109/ITSC.2019.8916853>
- [21] Boess et al. (2021) Digitalisation in Environmental Assessment: International frontrunners. Danish Centre for Environmental Assessment (DCEA), Aalborg University, Available at: https://vbn.aau.dk/ws/portalfiles/portal/467281294/DIGITALISATION_IN_ENVIRONMENTAL_ASSESSMENT_2.0.pdf
- [22] Bond (2024) Using an AI chatbot to critically review the scientific literature on the use of AI in Environmental Impact Assessment, Impact Assessment and Project Appraisal, 42(2), pp. 189-199, Available at: <https://doi.org/10.1080/14615517.2024.2320591>
- [23] Brokk (2024) Technology description, Available at: <https://www.brokk.com/industry/construction/>
- [24] Brzozowski et al. (2019) The use of low-cost sensors for air quality analysis in road intersections, Transportation Research Part D, pp. 198-211, Available at: <https://doi.org/10.1016/j.trd.2019.10.019>
- [25] Bruno S. et al. (2023) A Robotized Raspberry-Based System for Pothole 3D Reconstruction and Mapping, Sensors, 23(13), 5860, Available at: <https://doi.org/10.3390/s23135860>
- [26] Chatpdf (2024) Technology description, Available at: <https://www.chatpdf.com/>
- [27] Chavan S. et al. (2021) Vehicle Number Plate Recognition for Toll System, Advances in Intelligent Systems and Computin, 1162, Available at: https://doi.org/10.1007/978-981-15-4851-2_19
- [28] Copernicus (2024a) Europe's eyes on Earth, Available at: <https://www.copernicus.eu/en>

- [29] Copernicus (2024b) Flood risk assessment of the European road network, Available at: <https://nhess.copernicus.org/articles/21/1011/2021/>
- [30] DataFromSky (2024) Technology description, Available at: <https://datafromsky.com/traffic-monitoring/>
- [31] DREAMS (2024) Digitally supported Environmental Assessment for Sustainable Development Goals, Available at: <https://dreamsproject.dk/>
- [32] Dusty robotics (2024) Technology description, Available at: <https://www.dustyrobotics.com/solutions/mechanical>
- [33] eMOS (2024) Enhancing Motorway Operation Services, Available at: https://www.tii.ie/media/035ngh2m/d1_3_3_lewis_tii-annual-conference_2018_final_lewis-feely.pdf
- [34] Elistair (2024) Technology description, Available at: <https://elistair.com/monitoring-traffic-drone/>
- [35] EU AI Act (2024) – EU AI Act, Available at: <https://artificialintelligenceact.eu/ai-act-explorer/>
- [36] European Space Agency (2024) Land-cover maps of Europe from the Cloud, Available at: https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-2/Land-cover_maps_of_Europe_from_the_Cloud
- [37] EyeVi (2024) Technology description, Available at: <https://www.triona.eu/case/transport-infrastructure/triona-leads-the-way-for-oslo-municipality/>
- [38] Fjendbo, S. et al. (2023a), D4.1 Case study catalogue, INFRACOMS project, Available at: <https://static1.squarespace.com/static/62f3a10e333f08456dfb51d9/t/665f25171e908613e668295f/1717511455001/INFRACOMS+D4.1+Case+study+catalogue.pdf>
- [39] Fjendbo, S. et al. (2023b), D4.1 Case study report, INFRACOMS project, Available at: <https://static1.squarespace.com/static/62f3a10e333f08456dfb51d9/t/665f24d5f03b312eb274fb8b/1717511386301/INFRACOMS+D4.1+Case+study+report.pdf>
- [40] FLIR Thermicam (2024) Technology Description, Available at: <https://www.flir.eu/products/thermicam-ai/>
- [41] FOSS (2024), AI Playbook for Small States, Available at: <https://www.imda.gov.sg/-/media/imda/files/news-and-events/media-room/media-releases/2024/09/ai-playbook-for-small-states/imda-ai-playbook-for-small-states.pdf>
- [42] Fothergill, J. et al (2024) The State of Digital Impact Assessment Practice. A global review of the uptake of digital technologies and approaches within impact assessment practice, International Association for Impact Assessment (IAIA), Available at: https://iaia.org/downloads/State%20of%20Digital%20IA%20Practice_converted.pdf
- [43] Gaist (2024) Technology description, Available at: <https://www.gaist.co.uk>
- [44] Grau A. et al. (2019) Advances in Robotics Research: From Lab to Market. STAR, vol. 132, pp. 13–28. Springer, Available at: https://doi.org/10.1007/978-3-030-22327-4_2

- [45] Grabowski D. et al. (2020), System for monitoring road slippery based on CCTV cameras and convolutional NNs, Journal of Intelligent Information Systems, 55, pp. 521–534, Available at: <https://doi.org/10.1007/s10844-020-00618-5>
- [46] HawkEye (2024) Technology description, Available at: <https://www.he360.com/our-products/>
- [47] Hekič et al. (2022) Using B-WIM system-generated performance indicators to support model updating of a multi-span viaduct, Bridge Safety, Maintenance, Management, Life-Cycle, Resilience and Sustainability, 978-1-032-34531-4, Available at: <https://doi.org/10.1201/9781003322641-156>
- [48] iapp (2024) US State AI Governance Legislation Tracker 2024, Available at: https://iapp.org/media/pdf/resource_center/us_state_ai_governance_legislation_tracker.pdf
- [49] iappai (2024) Global AI Law and Policy Tracker, Available at: https://iapp.org/media/pdf/resource_center/global_ai_law_policy_tracker.pdf
- [50] iRASTE (2024) Intelligent Solutions for Road Safety through Technology & Engineering, Available at: <https://inai.iiit.ac.in/iraste-telangana.html>
- [51] iRASTE – Nagpur City Executive Summary. Available at: <https://inai.ai/wp-content/uploads/2024/04/iRASTE-Nagpur-Exec-Summary-SM.pdf>
- [52] iRASTE – Telangana Executive Summary. Available at: <https://inai.ai/wp-content/uploads/2024/10/Executive-Summary-iRASTE-Telangana.pdf>
- [53] ITF OECD (2021) AI in Proactive Road Infrastructure Safety Management, Available at: [AI in Proactive Road Infrastructure Safety Management \(itf-oecd.org\)](https://www.itf-oecd.org/ai-in-proactive-road-infrastructure-safety-management)
- [54] INFRARISK (2024) Integrated Assessment and Management of Infrastructure Risks, 2013-2016, Available at: <https://www.infrarisk-fp7.eu/>
- [55] Jensen J. et al. (2023) Digital transition in asset management of bridges - Advantages and challenges, Life-Cycle of Structures and Infrastructure Systems, 978-1-003-32302-0, Available at: <https://doi.org/10.1201/9781003323020-7>
- [56] Jin et al. (2015), Adaptive group-based signal control by reinforcement learning, Transportation Research Procedia, 10, pp. 207-216, Available at: <https://doi.org/10.1016/j.trpro.2015.09.070>
- [57] Kapsch TrafficCom (2024a), Technology description, Available at: <https://www.kapsch.net/en/press/releases/ktc-20220912-pr-en>
- [58] Kapsch TrafficCom (2024b), Technology description, Available at: <https://www.kapsch.net/en/traffic>
- [59] Keshtkaran E. et al. (2024), Estimating Blood Alcohol Level Through Facial Features for Driver Impairment Assessment, IEEE/CVF Winter Conference on Applications of Computer Vision, Available at: <https://ieeexplore.ieee.org/document/10484402>

- [60] Kommey et al. (2020) GhanaToll: Barrier-Free RFID Toll Collection and Management System for Ghana, *International Journal of Computer Applications*, 176(27), pp. 22-30, Available at: <https://doi.org/10.5120/ijca2020920278>
- [61] Labellerr (2024) Technology description, Available at: <https://www.labellerr.com/blog/enhancing-automated-vehicle-inspection-through-telematics-and-computer-vision-technology/>
- [62] Li et al. (2020) Adaptive Traffic Signal Control Model on Intersections Based on Deep Reinforcement Learning, *Journal of Advanced Transportation*, pp. 1-14, Available at: <https://doi.org/10.1155/2020/6505893>
- [63] Lovesey et al. (2023) Mobile Phone Detection Camera program: the New South Wales experience. *Australian Road Safety Conference 2023*, p.301-303. Available at: https://australasianroadsafetyconference.com.au/wp-content/uploads/2023/12/2023_ARSC_Full-Proceedings.pdf
- [64] Luleci et al (2022) Structural Health Monitoring of a Foot Bridge in Virtual Reality Environment, Available at: <https://www.sciencedirect.com/science/article/pii/S2452321622000683>
- [65] Maanpaa J. et al (2024) Dense Road Surface Grip Map Prediction from Multimodal Image Data, arXiv:2404.17324, Available at: <https://doi.org/10.48550/arXiv.2404.17324>
- [66] Malekjafarian et al. (2015) A Review of Indirect Bridge Monitoring Using Passing Vehicles, Shock and Vibration, article id 286139, pp. 1-16, <http://dx.doi.org/10.1155/2015/286139>
- [67] Mandirola M. et al. (2022) Use of UAS for damage inspection and assessment of bridge infrastructures, *International Journal of Disaster Risk Reduction*, 72, 102824, Available at: <https://doi.org/10.1016/j.ijdrr.2022.102824>
- [68] Marceddu A. et al. (2024) AI for Urban Safety: A Case Study for reducing road accident in Genoa, 8th International Conference on Smart Data and Smart Cities (SDSC), 4- 7 June 2024, Athens, Greece, Available at: <https://doi.org/10.5194/isprs-archives-XLVIII-4-W10-2024-131-2024>
- [69] McEvoy et al (2005) Role of mobile phones in motor vehicle crashes resulting in hospital attendance: a case-crossover study, *British Medical Journal*. Available at: <https://www.bmj.com/content/331/7514/428?ehom>
- [70] Mehra, R. et al.(2024) AssessAR: An Augmented Reality Based Environmental Impact Assessment Framework, *Proceedings of the 25th ACM Symposium on Virtual Reality Software and Technology*, Available at: <https://doi.org/10.1145/3359996.3365034>
- [71] Mei et al. (2019) Indirect health monitoring of bridges using Mel-frequency cepstral coefficients and principal component analysis, *Mechanical Systems and Signal Processing*, 119, pp. 523–546, Available at: <https://doi.org/10.1016/j.ymssp.2018.10.006>
- [72] Mico K. et al. (2023), Review of IoT Sensor Systems Used for Monitoring the Road Infrastructure, *Sensors*, 23(9), 4469, Available at: <https://doi.org/10.3390/s23094469>
- [73] Minge E. et al. (2020) Integrating Advanced Technologies into Winter Operations Decisions,

- [74] Nasar (2024) Technology description, Available at: <https://nisar.jpl.nasa.gov/mission/get-to-know-sar/interferometry/>
- [75] NIST (2024) AI Risk Management Framework, Available at: <https://www.nist.gov/itl/ai-risk-management-framework>
- [76] Nota AI (2024) Technology description, Available at: <https://www.renesas.com/us/en/document/prb/nota-ai-nota-dms?r=25462331>
- [77] NoTraffic (2024) Technology description, Available at: <https://notraffic.tech/how-it-works/>
- [78] Omicron project (2024) Key technologies, Available at: <https://omicronproject.eu/key-technologies>
- [79] Optibus (2024) Technology description, Available at: <https://blog.optibus.com/announcements/atap-optimizes-crew-and-vehicles-schedules-using-optibus>
- [80] Oracle Smart Construction Platform (2024) Technology description, Available at: <https://www.oracle.com/pt/construction-engineering/smart-construction-platform/>
- [81] Oracle Primavera Cloud (2024) Technology description, Available at: <https://www.oracle.com/uk/construction-engineering/primavera-cloud-project-management/>
- [82] Palanisamy et al. (2021) Drain Structural Defect Detection and Mapping Using AI-Enabled Reconfigurable Robot Raptor and IoRT Framework, Sensors, 21, 7287, Available at: <https://doi.org/10.3390/s21217287>
- [83] Pooya D. (2023), DT Enabled Winter Operations Management Through the Integration of AI, Sensory Level Data, and Publicly Available Data, Civil Engineering Dissertations. 436, Available at: https://mavmatrix.uta.edu/civilengineering_dissertations/436
- [84] PRECINCT (2024), Preparedness and Resilience Enforcement for Critical INfrastructure Cascading Cyberphysical Threats and effects with focus on district or regional protection, 2021-2023, Available at: <https://www.precinct.info/>
- [85] Q-Free Intrada Insight system (2024) Technology description, Available at: <https://www.q-free.com/product/intrada-insight/>
- [86] RAIN (2024), Risk Analysis of Infrastructure Networks in response to extreme weather, 2014-2017, Available at: <https://rain-project.eu/>
- [87] RESIST (2024) RESilient transport InfraSTructure to extreme events, 2018-2022, Available at: <https://www.resistproject.eu/>
- [88] Ricoh (2024) Frozen road detection technology description, Available at: https://www.ricoh.com/technology/tech/108_frozen_road_detection
- [89] Robotiz3d (2024) Technology description, Available at: <https://www.robotiz3d.com/university-of-liverpool-announces-the-spin-off-of-robotiz3d>
- [90] Salim M. et al. (2002) Artificial-Intelligence-Based Optimization of the Management of Snow Removal Assets and Resources, Midwest Transportation Consortium, Available at: https://rosap.ntl.bts.gov/view/dot/24539/dot_24539_DS1.pdf

- [91] SatSense (2024) Technology description, Available at: <https://satsense.com/what-is-insar>
- [92] SCATS (2024) Sydney Coordinated Adaptive Traffic System, Available at: <https://d1qosl6u8ngtyg.cloudfront.net/s3fs-public/file/cross-content/SCATS%20Core.pdf>
- [93] SCOOT (2024) Split Cycle Offset Optimisation Technique, Available at: <https://trlsoftware.com/products/traffic-control/scoot/>
- [94] Sensat (2024), Case studies, Available at: <https://www.sensat.co/case-studies/octavius-a46>
- [95] Siebert F. et al. (2020) Detecting motorcycle helmet use with deep learning, Accident Analysis and Prevention, 134, 105319, Available at: <https://doi.org/10.1016/j.aap.2019.105319>
- [96] Skycatch (2024a), Technology description, Available at: <https://blog.skycatch.com/2018/03/22/skycatch-and-dji-announce-global-agreement-to-deliver-high-precision-custom-drones-for-komatsu>
- [97] Skycatch (2024b), Technology description, Available at: <https://blog.skycatch.com/2016/09/21/dashboard-update-new-3d-viewers-map-sharing-links>
- [98] StreetScan (2024), Technology description, Available at: <https://streetscan.com/>
- [99] Suer A. et al. (2023), Development of an autonomous robotic snowplow for residential use, Proceedings of the ASME, International Mechanical Engineering Congress and Exposition, Available at: <https://doi.org/10.1115/IMECE2023-114010>
- [100] Skycatch (2024b), Technology description, Available at: <https://blog.skycatch.com/2016/09/21/dashboard-update-new-3d-viewers-map-sharing-links>
- [101] Suer A. et al. (2023), Development of an autonomous robotic snowplow for residential use, Proceedings of the ASME, International Mechanical Engineering Congress and Exposition, Available at: <https://doi.org/10.1115/IMECE2023-114010>
- [102] SurveyMonkey (2024) Platform description, Available at: <https://uk.surveymonkey.com/>
- [103] Sun et al. (2022), Deep Reinforcement-Learning-Based Adaptive Traffic Signal Control with Real-Time Queue Lengths, IEEE International Conference on Systems, Man, and Cybernetics, pp. 1760-1766, Available at: <https://doi.org/10.1109/SMC53654.2022.9945292>
- [104] Teleo and Storm equipment (2024), Technology description, Available at: <https://teleo.ai/blog/introducing-remote-operated-autonomous-snow-plow/>
- [105] The National Council for AI (2021), Egypt National AI Strategy, Available at: https://mcit.gov.eg/Upcont/Documents/Publications_672021000_Egypt-National-AI-Strategy-English.pdf
- [106] The White House (2024), Executive Order on the Safe, Secure, and Trustworthy Development and Use of AI, Available at: <https://www.whitehouse.gov/briefing->

[room/presidential-actions/2023/10/30/executive-order-on-the-safe-secure-and-trustworthy-development-and-use-of-artificial-intelligence/](https://www.whitehouse.gov/presidential-actions/2023/10/30/executive-order-on-the-safe-secure-and-trustworthy-development-and-use-of-artificial-intelligence/)

- [107] TM2.0 (2024), AI Act – TM2.0 Platform Position Paper, Available at: https://tm20.org/wp-content/uploads/2024/07/ERTICO-TM20_PositionPaper_AI-Act-Guidelines_FINAL_18122023.pdf
- [108] TrafiCam AI (2024) Technology description, Available at: <https://www.flir.co.uk/products/traficam-ai/?vertical=public+safety&segment=solutions>
- [109] Transcore (2024) Technology description, Available at: <https://transcore.com/tolling/infinity-digital-lane-system>
- [110] Trimble ProjectSight (2024) Technology description, Available at: <https://projectsight.trimble.com/product-projectsight/>
- [111] Trimble SiteVision GNSS (2024) Technology description, Available at: <https://sitevision.trimble.com/blog/augmented-reality-and-construction-an-overview>
- [112] Trimble Tekla (2024) Technology description, Available at: <https://www.tekla.com/uk/resources/blog/trimble-connect-and-hololens>
- [113] Universeoptics (2024) Technology description, Available at: <https://www.universeoptics.com/>
- [114] University of Minnesota Robotics (2024) Technology description, Available at: <https://studentrobotics.umn.edu/snowplow>
- [115] Valido M. et al. (2023) Consumption Based on AI Camera System and Gas Emission Estimator Model, Sensors, 23(1), 312, Available at: <https://doi.org/10.3390/s23010312>
- [116] Valerann LinkedIn (2024) Lanternn Interface, Available at: <https://www.linkedin.com/products/valerann-lanternn-by/>
- [117] Van Geem C. et al. (2023) NRAs' Benefits and Challenges Whilst Implementing Innovative and Future-proof Road Asset Condition Monitoring Systems in Asset Management Decision, WRC 2023 Conference, Available at: <https://static1.squarespace.com/static/62f3a10e333f08456dfb51d9/t/665f2836ed99ca61bd9f5456/1717512248168/WRC+2023+paper+IP0329+INFRACOMS.pdf>
- [118] VíaSegura (2024) Technology description, Available at: <https://irap.org/rap-tools/light-ratings/viasegura/>
- [119] Vimeo ibtta (2024) Data Utilization to Improve Operational Effectiveness, Available at: [Data Utilization to Improve Operational Effectiveness on Vimeo](#)
- [120] Wall et al. (2019) The testing and evaluation of a vision based automatic detection system for illegal phone use by drivers in Australia. Available at: [Microsoft Word - ARSC2023 Proceedings Part 1, Preface, DRAFT](#)
- [121] Wavetronix SmartSensor Matrix (2024) Technology description, Available at: <https://www.universeoptics.com/surveillance-cameras-monitor-traffic/>

- [122] White Case (2024), AI Global Regulatory Tracker, Available at: <https://www.whitecase.com/insight-our-thinking/ai-watch-global-regulatory-tracker#articles>
- [123] White House (2024) White House memorandum “Advancing Governance, Innovation, and Risk Management for Agency Use of AI.”, Available at: <https://www.whitehouse.gov/wp-content/uploads/2024/03/M-24-10-Advancing-Governance-Innovation-and-Risk-Management-for-Agency-Use-of-Artificial-Intelligence.pdf>
- [124] Workman R. et al. (2023) Prediction of Unpaved Road Conditions Using High-Resolution Optical Satellite Imagery and ML, Remote sensing, 15(16), 3985, Available at: <https://doi.org/10.3390/rs15163985>
- [125] World Bank (2021) World Bank Country and Leading groups, Available at: <https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups>
- [126] Xie L. et al. (2018), A New CNN-Based Method for Multi-Directional Car License Plate Detection, IEEE Transactions on ITS, 19(2), pp. 507-517, Available at: <https://doi.org/10.1109/TITS.2017.2784093>
- [127] XYZ Reality (2024), Technology description, Available at: <https://www.xyzreality.com>
- [128] Zhao Z. et al. (2020), Driver Fatigue Detection Based on Convolutional NNs Using EM-CNN, Computational Intelligence and Neuroscience, Article ID 7251280, Available at: <https://doi.org/10.1155/2020/7251280>

APPENDIX A: AI CATEGORISATION APPROACH

Table A.1: Categories used to evaluate and group AI technology application to the road sector.

Category	Categorisation Options
Activity	Planning, feasibility, route selection, appraisal; Resilience planning; Environmental impact assessment; Road infrastructure design; Construction; Project management; Road operations, traffic, and incident management; Tolling; Winter services and management; Road safety; Asset management; Infrastructure inspection and monitoring; Infrastructure maintenance and repairs; Policy development; Finance, funding, and procurement; Other
Life cycle stage	Planning; Conceptualisation; Design; Construction; Operation; Maintenance; Demolition; Disposal
Asset type	Earthworks; Pavements; Structures; Road drainage; Cycle/ pedestrian infrastructure; Road furniture; ITS Equipment; Other
Data set (input/output)	Traffic accident data; Pavement and structure condition; Condition of other assets (signs, road markings, barriers, etc.); Condition of ITS assets; Traffic data; Floating vehicle data; Road weather data; Spatial/GIS data for roads/assets; "As-built" data for roads/assets; Road network performance metrics; Customer satisfaction data; Air and noise pollution data; Data for road upgrade/improvement business cases; BIM data for construction sites; Other
Benefit	Cost savings; Time savings; Environmental benefits; Improvements in network performance; Improvements in road safety; Improved asset management; Enhanced infrastructure inspection efficiency / accuracy; Improvements in maintenance practices; Improved efficiency in administrative processes; Other
Benefit level	Unclear; Low; Medium; High
Benefit kind	Operational benefits to NRAs/ ROs; Societal benefits (please refer to their definition in section 2.2)
Risk, barriers and implementation challenges	Financial barriers/implementation costs; Legal/regulatory issues; Data issues (privacy, cybersecurity, sharing); Technical issues; Lack of pilot tests; Risk of reducing human expertise; Lack of accurate datasets; Lack of trust in AI; Insufficient supporting infrastructure (ITS, data centres, etc.); Resistance to innovation; Organisational change challenges; Shortage of skilled workforce; Fear of job replacement; Other
Risk, barriers and implementation challenges level	Unclear; Low; Medium; High
Legislation, regulations, policies or practices	Unclear; Yes; No
Implementation timeline (maturity)	Unclear; Already in the market; 2025 - 2030; After 2030
Technology type	Sensor Technologies; Remote Sensing; Imaging and Vision Technologies; Data Processing and Analytics; Human-Computer Interaction and User Experience; Autonomous robots; Other
Effectiveness (reliability / accuracy)	Unclear; Low; Medium; High
Purchase cost	Unclear; Low; Medium; High
Installation cost	Unclear; Low; Medium; High
Maintenance cost	Unclear; Low; Medium; High

APPENDIX B: LITERATURE REVIEW: DETAILED FINDINGS

This appendix presents a detailed analysis of the literature review findings across all road activities examined in this study, as outlined in Table A.1. It serves as a supplement to the summary of key findings provided in Section 3.16.

AI IN ROAD SECTOR: DEVELOPMENTS TO 2030

9.1.1. Planning, feasibility, route selection, appraisal

The literature review collected in this work indicates that advanced AI-driven algorithms for data analysis and predictive modelling are the primary AI technologies employed in planning, feasibility assessment, route selection, and appraisal within the road sector. These technologies are utilised to inform and optimise design, forecast traffic patterns, and analyse geographical features. Key benefits of these technologies include providing tailored decision-making support for road planners and authorities concerning feasibility assessments and route selection processes.

For instance, Bentley's OpenRoads ConceptStation software, which is commercially available, empowers highway engineering professionals to create conceptual road and bridge designs rapidly, utilising extensive data sets, including geographical information, environmental constraints, and economic factors (Bentley OpenRoads, 2024). This software facilitates the creation of intelligent digital models in a real-world context by integrating data-rich terrain models, Geographical Information System (GIS) data, and imagery with advanced parametric modelling and engineering sketching tools. These features enable the evaluation of multiple design alternatives and associated costs, improving decision-making in the early stages of road planning.

Although OpenRoads ConceptStation does not directly employ AI or ML technologies, it incorporates highly automated processes to streamline the conceptual design phase. For example, it uses adaptive tools that comply with AASHTO standards for road geometry, allowing users to quickly generate road alignments, intersections, and bridge designs that meet predefined specifications. Furthermore, the software's simulation capabilities and cost estimation tools enable planners to assess potential high-cost items and risks, which are crucial for selecting optimal design scenarios.

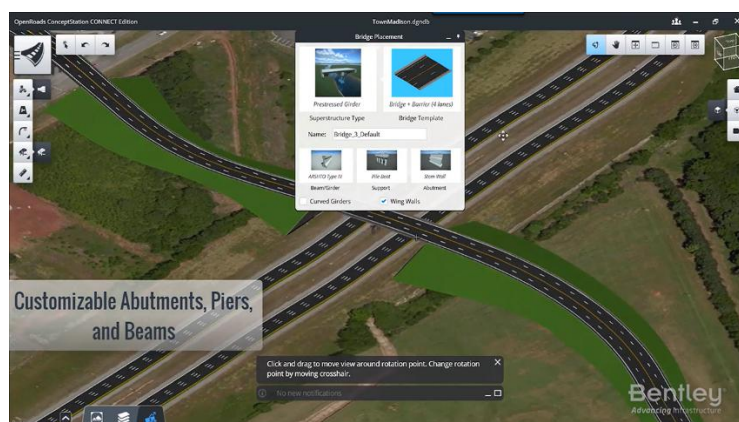


Figure B.1: Advanced algorithms, and predictive modelling enhance planning, feasibility, and route selection in road projects, leading to better early-stage decisions (Bentley OpenRoads, 2024).

The platform also integrates immersive visualisation features, such as real-time rendering using the LumenRT engine, which enhances collaboration with stakeholders by providing cinematic-quality presentations of conceptual designs in a virtual 3D environment. This capability allows engineers to convey project impacts clearly, improving stakeholder engagement and increasing the likelihood of approval for proposed designs. While it does not integrate AI, its ability to process large volumes of geospatial and engineering data and produce optimised results makes it an indispensable tool in the road sector. Figure B.1 presents a snapshot of the interface for this system.

Advanced data-driven simulation models in conjunction with ML algorithms and predictive analytics can also be utilised to analyse and forecast traffic patterns and infrastructure performance. For example, Aimsun's simulation models recreate traffic flow scenarios using real-time and historical data, allowing the software to assess the impact of different planning and design options (see Figure B.2) (Aimsun, 2024). Then, ML algorithms enhance these simulations by identifying patterns and trends in the data, which helps in predicting future traffic conditions. Predictive analytics based on these insights can then be used to evaluate the feasibility of various routes and scenarios, supporting informed decision-making in road planning and appraisal.

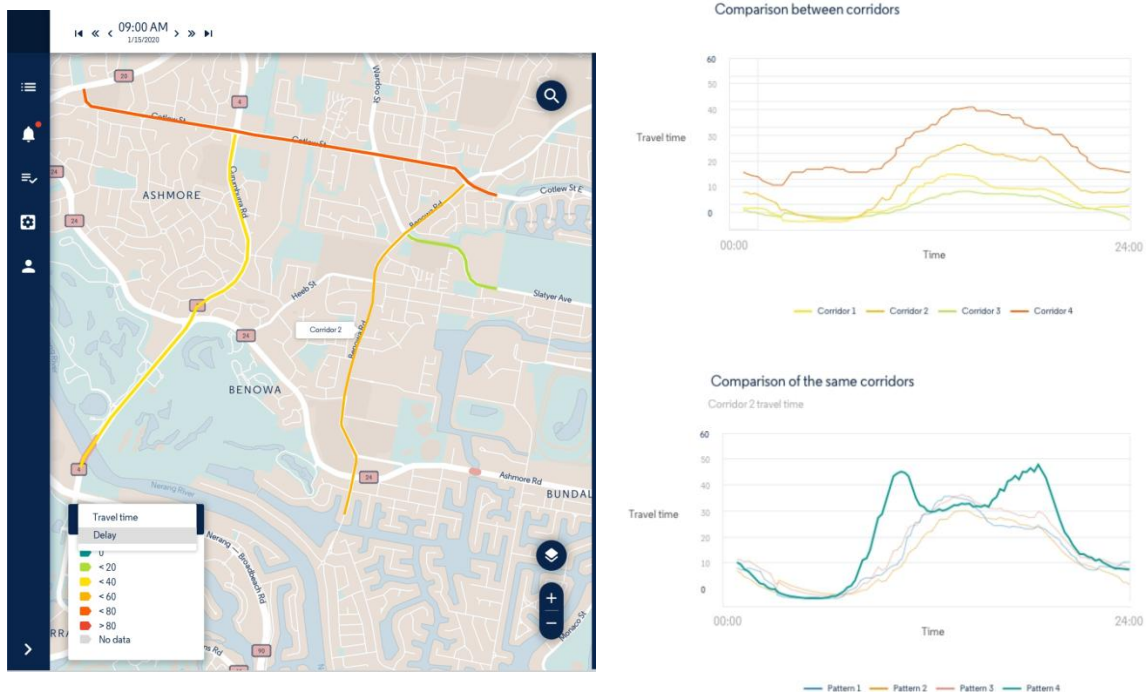


Figure B.2: AI-driven simulation models, ML, and predictive analytics forecast traffic patterns and assess design impacts, aiding effective road planning and appraisal (Aimsun, 2024).

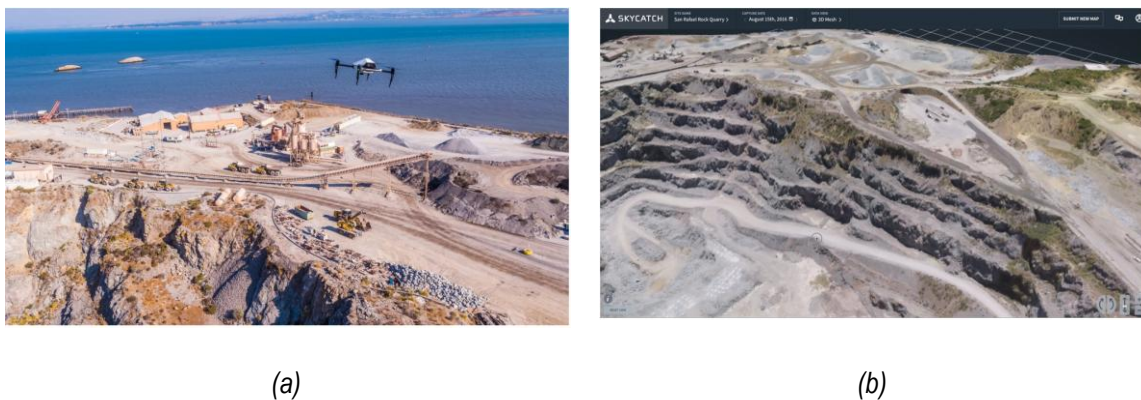


Figure B.3: AI-driven image processing, ML, and 3D reconstruction from drone data create detailed topographical models, improving the precision of road planning. (a) site location, (b) 3D reconstruction in Skycatch software (Skycatch, 2024a and 2024b).

Advanced image processing, ML and 3D reconstruction algorithms are also used in road planning. These technologies work together to analyse aerial imagery and Light Detection and Ranging (LiDAR) data captured by drones. An example of this AI technology is illustrated in Figure B.3. ML algorithms enhance image recognition and feature extraction, enabling the software to identify and classify terrain types, vegetation, and other environmental factors. The 3D reconstruction algorithms then convert the processed data into detailed and accurate topographical models. This integration of AI technologies allows for precise analysis of geographical features, aiding in planning of road infrastructure projects.

9.1.2. Resilience planning

The literature review revealed that data processing and analytics, combined with ML algorithms, are critical applications of AI in resilience planning. These technologies assimilate extensive historical and real-time data to forecast, assess, and mitigate risks associated with road infrastructure. For instance, predictive analytics are crucial for forecasting the impacts of severe weather events on road infrastructure. Analysing of historical weather data, traffic patterns, and infrastructure performance metrics, predictions can generate predictions about how various scenarios might affect road resilience.

In the European region, several research projects have been initiated to develop key performance indicators for resilience planning. A summary of these key research projects is provided in Table B.2. The software tools employed in these studies have been validated through case studies in various European regions, but they remain the subject of ongoing research.

Table B.2: European research projects which used predictive analytics to forecast severe weather impacts on road and other critical infrastructure to facilitate resilience planning.

Research project	Year	Summary
Preparedness and Resilience Enforcement for Critical INfrastructure Cascading Cyberphysical Threats and effects with focus on district or regional protection (PRECINCT)	2021-2023	The PRECINCT project used digital technologies such as digital twins for real-time infrastructure monitoring, collaborative management tools for cross-facility coordination, and serious game-based algorithms for vulnerability assessment to strengthen road sector resilience against cyber-physical threats and natural hazards (PRECINCT, 2024).
RESilient transport InfraSTRUCTure to extreme events (RESIST)	2018-2022	The RESIST project utilised technologies such as robotics for inspection, predictive analytics for damage forecasting, real-time data integration for communication, and cybersecurity solutions to enhance road infrastructure resilience against extreme events (RESIST, 2024).
Risk Analysis of Infrastructure Networks in response to extreme weather (RAIN)	2014-2017	The RAIN project used advanced numerical models for early warning systems, predictive analytics for decision support, and optimisation algorithms to enhance road sector resilience against extreme weather events (RAIN, 2024).
Integrated Assessment and Management of Infrastructure Risks (INFRARISK)	2013-2016	The INFRARISK project resulted in advanced models for simulating and predicting infrastructure vulnerabilities. It also integrated dynamic uncertainty into risk assessments, and enabled collaborative platforms for sharing and analysing data, all aimed at enhancing road sector resilience against rare and extreme events (INFRARISK, 2024).

Argyroudis et al. (2024) also investigated how emerging digital technologies can support climate resilience of critical infrastructure, including road networks. The study highlighted the importance of AI-driven tools and DTs in enhancing resilience planning through predictive analytics, real-time monitoring, optimised resource allocation, and scenario simulation. The study also compared traditional management ramifications vs emerging digital technologies for enhancing different phases of life-cycle climate resilience. This are also shown in Figure B.4.

emerging technologies enhancing different phases of the life-cycle climate resilience				
phase of resilience	traditional management ramifications	emerging digital technology	resilience enhancement - example	
A plan prepare	climate change leading to decrease of performance reduced knowledge of ageing, accelerated deterioration, increased demand	building information modelling (BIM) digital twins data analytics machine learning & artificial intelligence (AI) agent-based modelling	5G internet of things (IoT) structural health monitoring (SHM)	climate preparedness, including the impact of multiple stressors better understanding of interdependencies accurate evaluation of infrastructure exposure update of hazard models
B absorb respond	excessive losses due to inadequate preparedness and high vulnerabilities	phone metadata crowdsourcing social media data analytics unmanned aerial vehicle (UAV) light detection and ranging (LiDAR)		reduced losses due to early warnings or monitoring of interoperabilities
C recover	delayed commencement of recovery due to uncertainties in understanding asset condition slow recovery due to inefficient prioritization and allocation of resources	UAV LiDAR satellites aerial imagery machine learning & AI		smaller idle time due to rapid post-disaster assessment fast recovery by guiding response drones using machine learning for damage detection
D adapt	inadequate information for asset performance and interdependencies subjective allocation of resources	agent-based modelling augmented and mixed reality sensors from connected vehicles		data-driven adaptation enhanced by innovative/sustainable solutions monitoring of infrastructural, technological, social, informational, and environmental interdependencies prevent cascading threats

Figure B.4: Traditional management ramifications vs emerging digital technologies for enhancing different phases of life-cycle climate resilience (Argyroudis et al., 2024).

The literature review also indicated that remote sensing and imaging technologies are crucial for informing AI technologies used in resilience planning. Notable examples include Copernicus - Europe’s Eyes on Earth (Copernicus, 2024a & 2024b) and the European Space Agency (ESA, 2024), which are both under active use and development. These technologies facilitate continuous monitoring of infrastructure conditions.



Figure B.5: Satellite land use and land cover data which are used with ML algorithms to inform changes in land use and environmental factors e.g. erosion or vegetation growth affecting road stability (ESA, 2024).

For example, they detect changes in land use (see Figure B.5), flood risk (see Figure B.6), and other environmental factors that impact road stability. Then, AI models assess weather patterns and infrastructure health, predicting potential vulnerabilities and disruptions. This proactive approach optimises maintenance schedules and enhances response strategies to extreme weather and natural hazards, thereby reinforcing the resilience and robustness of road networks.

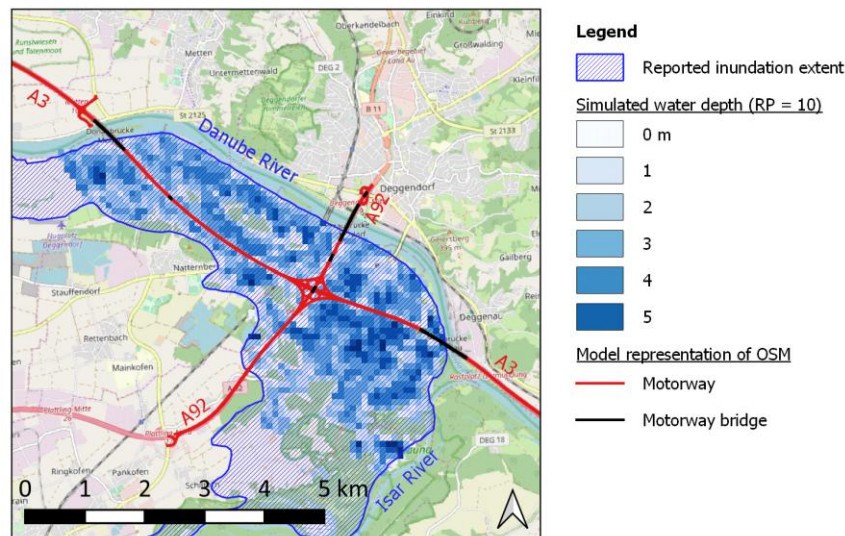


Figure B.6: Observed and simulated flood in Deggendorf, Germany. AI-driven algorithms are utilised to predict vulnerabilities and optimising maintenance and response to extreme weather (Copernicus, 2024).

9.1.3. Environmental impact assessment

The literature review demonstrated that AI-driven algorithms are the primary AI technology used in Environmental Impact Assessment (EIA). These algorithms can analyse vast datasets from previous projects to identify potential environmental risks and mitigation measures. This can also result in significant time savings.

Another AI technology for EIA are digital screening tools which can be utilised to streamline the initial evaluation of road proposals, determining whether a full EIA is necessary. Finally, it has been identified from the literature that remote sensing technologies in conjunction with AI-driven analytics can be used to monitor environmental changes in road infrastructure, allowing compliance with environmental regulations to be monitored and enhancing decision-making processes throughout the project lifecycle. Next paragraphs detail these technologies through real world research projects and commercial products.

For example, the DREAMS project (Digitally Supporting Environmental Assessment for Sustainable Development Goals) harnessed the power of AI to transform the EIA process in Denmark (Boess et al. 2021). At its core, the project sought to consolidate dispersed EIA reports into a unified, digital repository, previously scattered across various platforms. These reports were systematically collected, allowing for easier access and analysis. AI-driven algorithms exploited storing metadata alongside the reports to facilitate the extraction of key information, streamlining the use of historical data to inform future assessments.

A critical element of the DREAMS project was the enhancement of an existing environmental baseline tool. This tool used ML algorithms to automatically gather data from EIA reports, environmental studies, and research articles, providing a more efficient means of conducting baseline studies. The tool also integrated GIS technology, to allow users to identify environmental conditions within specific regions, supporting more precise decision-making.

The CAUSA tool represented another significant advancement, as it identified cause-effect relationships between activities and their environmental impacts using AI-driven data analytics.

This tool was linked to the baseline system and GIS data, helping authorities assess risks and mitigation strategies. Through these innovations, the DREAMS project aimed to enhance the effectiveness of environmental planning and promote sustainable development. Figure B.7 illustrates the DREAMS project tools, main objectives and results.

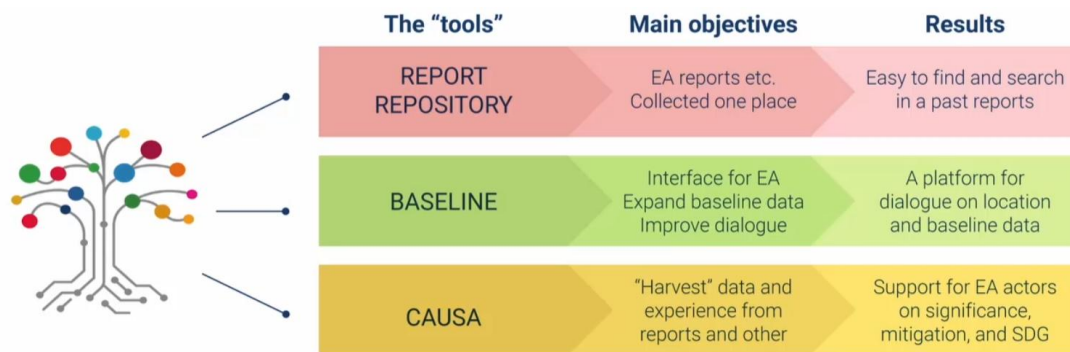


Figure B.7: The DREAMS project used AI to digitise environmental reports, enhancing access, analysis, and planning with AI, GIS, and CAUSA tools. (DREAMS, 2024).

Large Language Models (LLMs) represent a key AI technology which uses sophisticated ML algorithms to process and understand text within documents with good accuracy. Although this AI technology is relatively new, it has demonstrated significant time savings in reviewing scientific documents. In the realm of road sector, this technology can be used to synthesise extensive volumes of documents, highlighting key findings and methodologies. For example, Bond et al. (2024) explored the capabilities of AI-driven chatbots to critically review scientific literature related to EIA. Its use can significantly reduce the time required for literature review and facilitate a thorough examination of regulatory and ethical considerations. This, in turn, supports more informed decision-making in environmental management and road sector assessments. Figure B.8 presents an example of document reviewing through Chatpdf platform.

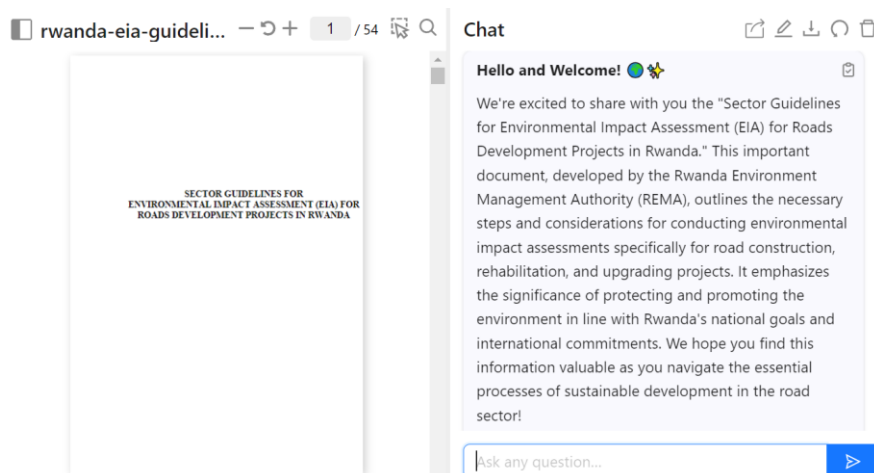


Figure B.8: LLMs enhance the review of documents, resulting in significant time savings (Chatpdf, 2024).

AR technology is increasingly being explored for its potential to enhance EIA by providing immersive and interactive experiences. This is investigated in the research work of Mehra et al., (2019). The AI component of AR involves generative AI, which aids in creating dynamic scenes and simulating project impacts in real-time. This technology allows stakeholders to visualise project impacts by

overlaying digital information onto the physical environment, enabling better understanding and communication of potential effects. For example, Figure B.9 depicts the auditor's field-of-view during an EIA, using voice commands to analyse terrain, bird migration paths, nearby buildings, and simulating a bridge's impact, before communicating concerns to a stakeholder.

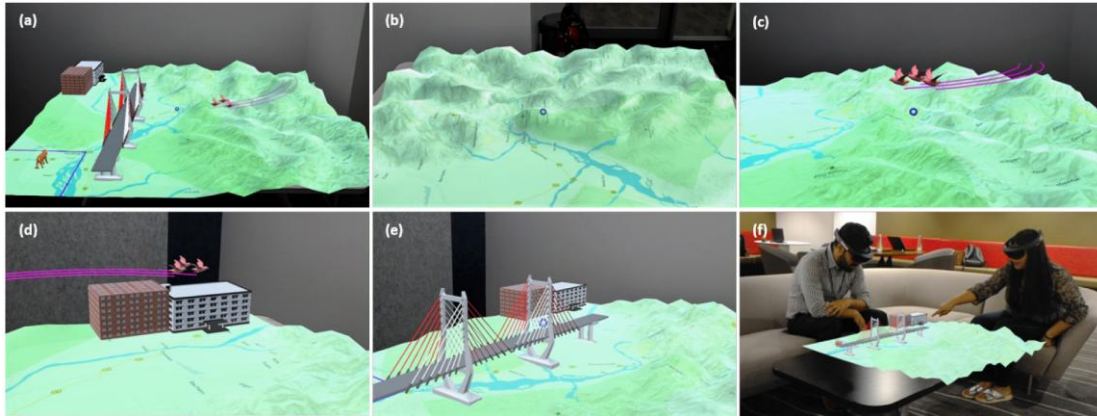


Figure B.9: An auditor evaluates a bridge project's impact on bird migration, considering: (a) environment, (b) terrain, (c) migration routes, (d) structures, (e) construction, and (f) stakeholders (Mehra et al., 2019).

The literature review also identified an AI technology capable of analysing Radio Frequency (RF) signals captured by satellites to enable detailed monitoring of environmental conditions around road networks (HawkEye, 2024). In particular, AI-driven algorithms process and interpret RF data to identify patterns and anomalies that may indicate environmental disturbances, such as unauthorised land use or activities impacting surrounding ecosystems (see Figure B.10). Hence, this technology supports EIA by providing precise, real-time insights into how human activities influence the environment in areas affected by road infrastructure.

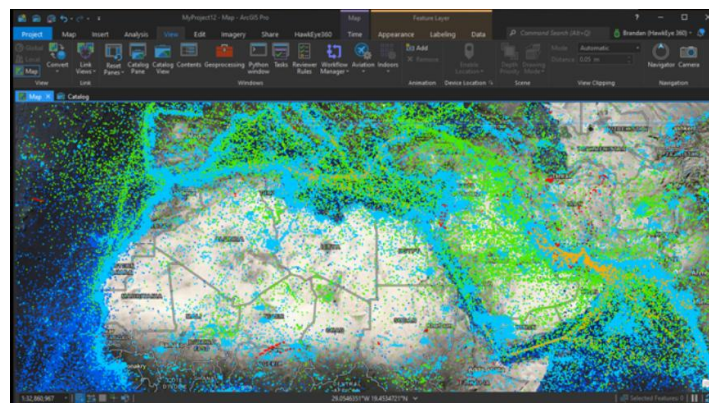


Figure B.10: AI analyses satellite RF signals to monitor road networks, detect disturbances, and provide real-time insights for impact assessments (HawkEye, 2024).

9.1.4. Road infrastructure design

The literature review indicated that AI technologies in road infrastructure design primarily include AI-driven algorithms for rapid exploration and optimisation of road layouts based on user requirements. However, examples of AR or Mixed Reality (MR) systems have also been identified which visualise 3D models of the design on physical sites. In addition, AI-driven generative design algorithms represent an emerging technology in engineering design, as they can generate

innovative geometric configurations by simulating scenarios and refining designs to meet functional and environmental goals.

The literature review suggests that algorithms enable the rapid exploration of design alternatives and automated road parameter adjustments based on evolving project requirements. For instance, Figure B.11 illustrates this technology in optimising road design layouts using the commercially available software, Bentley GenerativeComponents. This facilitates the creation of intricate road networks that meet engineering standards while optimising for factors such as terrain and traffic flow. However, Bentley GenerativeComponents relies on rule-based parametric design, using scripting for complex geometry but lacking native AI for optimisation.

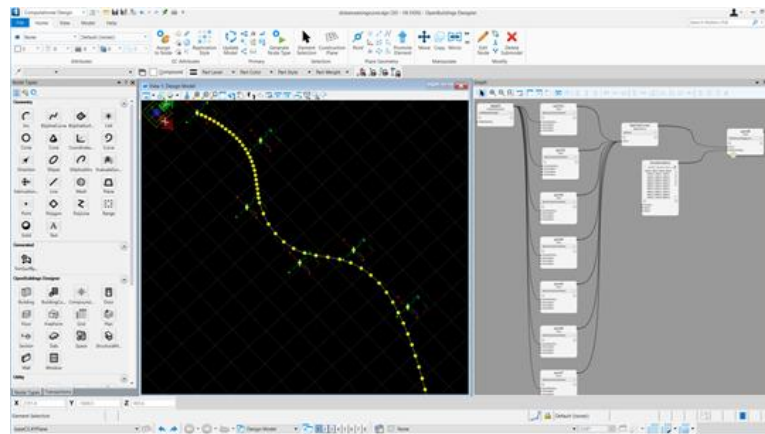


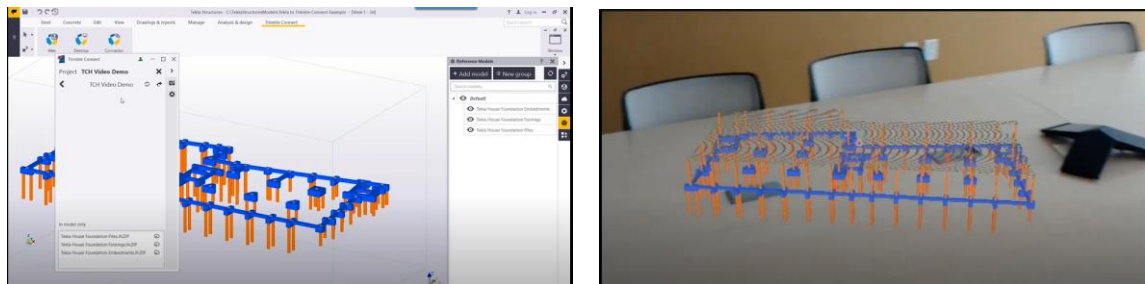
Figure B.11: Rule-based parametric design algorithms explore designs and auto-adjust road parameters to optimise complex networks for terrain, traffic flow, and more (Bentley GenerativeComponents, 2024).

In addition, it was found in the literature that road infrastructure design can be improved through AR systems. For example, these systems can combine Global Navigation Satellite System (GNSS) technology with AR to provide real-time, georeferenced visualisations of infrastructure projects such as Trimble SiteVision GNSS commercially available technology (Trimble SiteVision GNSS, 2024). This technology overlays 3D models on physical sites, enhancing spatial awareness and accuracy in road design, construction, and maintenance, thereby improving operational efficiency and stakeholder collaboration. Figure B.12 demonstrates an example of AR system for a bridge design using the Trimble SiteVision GNSS technology.



Figure B.12: GNSS-integrated AR enhances spatial awareness and precision in road design, as shown in the A14 Cambridge to Huntingdon project with Trimble SiteVision (Trimble SiteVision GNSS, 2024).

In addition to the above technology, it was also found in the literature that AI-driven visualisation tools, integrated with MR, project digital content as holograms during meetings, offering stakeholders immersive previews of design proposals, enhancing communication and understanding, and improving public consultation with clear, accessible representations of proposed changes. Figure B.13 illustrates this technology through the commercially available Trimble Tekla product.



(a)

(b)

Figure B.13: AI-driven visualisation tools offer holographic previews, enhancing stakeholder communication and public consultation with clear representations (Trimble Tekla, 2024).

Another emerging AI technology that was identified from the literature was AI-driven generative design of structural components. It is a recently available AI technology which employs advanced algorithms to generate optimal geometric configurations of structural components. This AI technology begins by defining design goals, such as minimising material use or enhancing safety. It then generates multiple design solutions by analysing various parameters and constraints. The system simulates different scenarios and evaluates each design against the predefined goals, producing innovative road designs that might not be intuitive to human planners. Through iterative processes, the technology refines and optimises these designs, ensuring that the final output meets both functional and environmental requirements effectively. An example of Generative design is shown in Figure B.14 through the commercially available product Autodesk Generative Design.

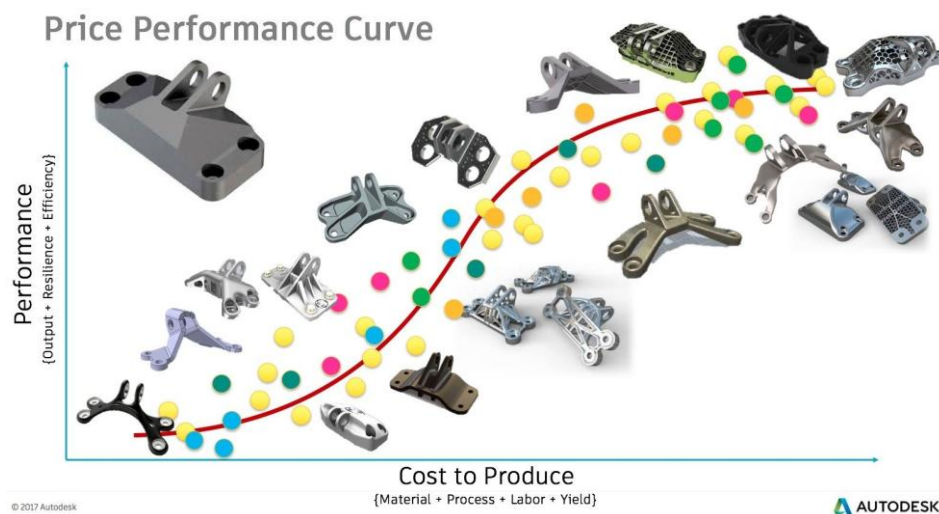


Figure B.14: Generative design optimises structural components using algorithms to analyse goals and constraints through iterative simulations (Autodesk Generative Design, 2024).

9.1.5. Construction

It was identified in the literature that many AI technologies in construction operate on the basis of a comprehensive DT. DTs offer a dynamic 3D representation that amalgamates various datasets related to the construction of the project. It can integrate real-time data from multiple sources, such as sensors and surveys, to monitor construction progress and detect clashes between different elements of the design. To this extent, AI-driven algorithms enable early identification of potential issues, enhance planning accuracy, and support improved construction workflows. They can also improve communication among stakeholders, fostering real-time discussions and informed decision-making and therefore reducing the necessity for frequent site visits.



Figure B.15: A46 Binley project. Sensat's timeline feature used for remote progress monitoring during construction (Sensat, 2024).

Figure B.15 and Figure B.16 present such an example in A46 Binley project in Coventry, U.K. (Sensat, 2024a). In March 2020, the construction of a new A46 flyover at Binley junction near Coventry has begun to separate local traffic and reduce congestion. The construction company, Octavius Infrastructure, in partnership with Sensat used advanced data capture technology to create 2D and 3D DTs of the site. This enabled real-time monitoring throughout the construction stage, helping manage the complex site while ensuring traffic flow and maintaining strict safety protocols (see Figure B.15).

This DT technology also enabled the construction company to prioritise safety by allowing remote site access and minimising physical visits. Instead of frequent on-site checks, teams used the virtual replica to analyse project data and make informed decisions, enhancing safety and operational efficiency. These measurement tools enabled accurate planning for traffic management and temporary works, reducing time spent on-site. In a summary report, Sensat stated that over 800 markups have been made, saving 7.4 tonnes of CO₂ by cutting down site visits and optimising traffic management planning (Sensat, 2024).



Figure B.16: Sensat optimised traffic management for the A46 Binley project, reducing site time, improving planning, and saving 7.4 tonnes of CO₂ with 800+ mark-ups (Sensat, 2024).

The literature review has also revealed another common technology application in the construction phase, i.e. AR. The AI component of AR in construction typically involves ML algorithms that enhance object detection, alignment, and tracking capabilities. These capabilities allow AR devices to project detailed 3D designs onto the site with precision, ensuring accurate alignment and verification of construction elements. This technology follows the same concept as explained in Figure B.12. AR helps construction teams to enhance spatial awareness and identify discrepancies between the digital model and actual site conditions, facilitating accurate execution and adjustments. This improves coordination, reduces errors, and supports construction processes by enabling real-time, visual feedback. An example of this AI technology is demonstrated in Figure B.17 through the commercially available XYZ Reality product. The use of XYZ reality technology has led to up to 9X return on investment for certain projects.

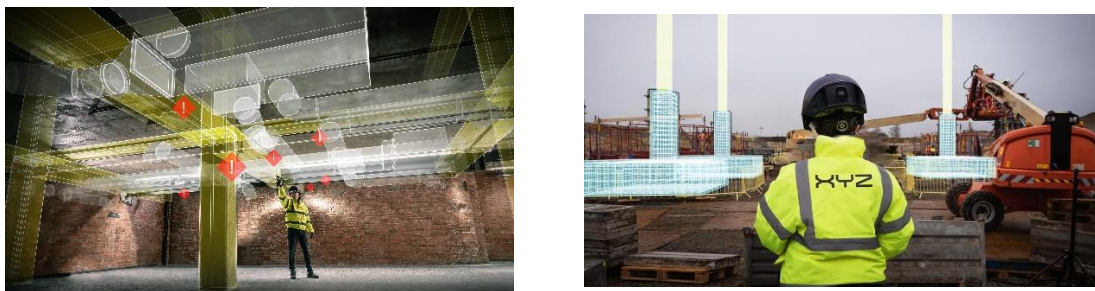
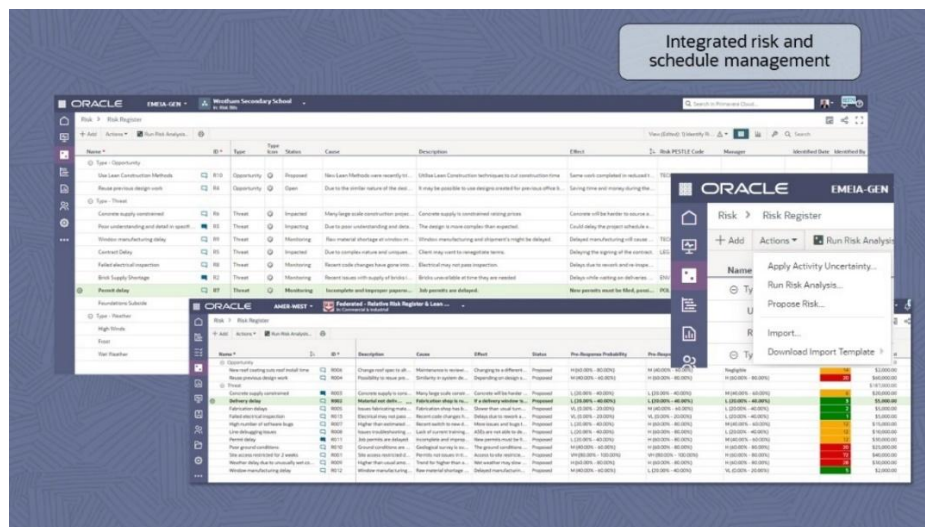


Figure B.17: Construction with AR (XYZ Reality, 2024).

In addition, it has been found that predictive analytics can enhance construction management and execution capabilities through the integration of various data sources. For example, advanced algorithms can be employed to analyse real-time data, such as construction progress and resource utilisation, and can provide actionable insights. This technology enables the detection of potential issues before they arise, optimises scheduling and resource allocation, and facilitates data-driven decision-making. Hence, it facilitates automation in construction workflows and improves overall construction efficiency. Commercial products which utilise this technology are available in the market such as Oracle Smart Construction Platform. Figure B.18 demonstrates the interface of this platform. However, it is also evident that the concept of this technology can be generalised in project and portfolio management activities of any complex projects (see e.g. Oracle Primavera Cloud product).



Another example of AI application in the construction stage is the use of autonomous robots which are able to perform precise demolition and construction tasks. While this AI technology has reached a reasonable level of maturity at the component level, such as in individual robotic systems equipped with sensors and navigation capabilities, integration of these systems into broader road traffic management systems and construction procedures remains less substantive. This highlights an ongoing challenge in achieving seamless system-level adoption and optimisation, particularly in complex construction and traffic environments. Nonetheless, there are commercial products available demonstrating the potential of this technology.

These autonomous robots are equipped with sensors and navigation systems to operate independently, handling tasks such as breaking concrete, removing debris, and performing heavy lifting with high accuracy. Figure B.19 illustrates an example of a commercially available autonomous robot used during demolition. Those systems are also able to analyse their environment in real-time, and execute tasks according to pre-set plans, improving construction/demolition safety and efficiency. The literature review indicated that the main benefit of this technology is the process automation, which in return reduces manual labour, enhances precision and worker safety, and accelerates project timelines. Another key benefit associated with the use of automated robots in construction is the increased safety that is provided for workers, these

robots can complete tasks which may be considered hazardous for workers such as excavation and earthmoving works.

Industry reports indicate that robotic systems, such as the Dusty Robotics FieldPrinter (Dusty robotics, 2024), are used to automate the layout and marking of construction sites. These systems employ advanced sensors and AI algorithms to transfer digital design plans onto the physical site with high precision. The FieldPrinter operates by integrating with BIM software, to accurately project and print layout lines based on the latest digital models. It autonomously positions itself and uses pre-set coordinates to mark construction lines and reference points. This technology automates the layout process, reducing manual labour and minimising errors, while also accelerating overall progress. Figure B.20 illustrates this technology in action.



Figure B.20: AI-powered robotic systems automate the layout and marking of construction sites with high precision, reducing manual labour, minimising errors, and speeding up the process (Dusty robotics, 2024).

9.1.6. Project management

Various examples of AI technology in project management illustrate its transformative impact. The literature reviewed highlights that advanced algorithms are used to optimise different aspects of project execution. Predictive algorithms enhance project management planning by forecasting potential delays and resource requirements through historical data analysis. They also improve scheduling by dynamically adjusting timelines based on real-time progress and unexpected disruptions. Resource allocation is enhanced as AI evaluates the availability and efficiency of personnel and materials, ensuring optimal utilisation. Additionally, AI supports project managers in making informed decisions by analysing patterns and generating actionable insights. This ultimately drives efficiency and cost-effectiveness in road construction and maintenance projects.

This technology has reached a good level of maturity, and there are several commercial products which are able to perform these tasks, e.g. Trimble ProjectSight (see Figure B.21), Oracle Primavera Cloud product, etc. Many of these AI-based project management tools depend on the availability of digital plans and invoicing systems to function effectively. These digital inputs provide the structured data required for AI algorithms to optimise scheduling, resource allocation, and financial tracking. Organisations seeking to adopt such technologies should ensure that their workflows incorporate digital documentation to fully leverage the benefits of AI.

Trimble PROJECTSIGHT

University Student Union & Wellness Center > Field Management > Checklists

Viewing 23 Checklists

Number	Revision	Subject	Status	Module	Template
001	01	Irish Concrete	Approved	Other	Subcontractor Startup ...
002	01	Campos Construction	Approved	Other	Subcontractor Startup ...
003	01	GLXC Inspector's Daily...	Pending Appr...	QA/QC	Inspectors Daily Report ...
005	01	Fixture Delivery	Approved	Deliveries	Plumbing Fixtures
006	01	Fixture Deliveries	Approved	Deliveries	Plumbing Fixtures
007	01	Plumbing Stuff	Open	Deliveries	Plumbing Fixtures
008	01		Pending Appr...	Commissioning	Blower Inspection
009	01	DD348	Pending Appr...	QA/QC	Fireproofing Checklist
009	02	DD348	Approved	QA/QC	Fireproofing Checklist
010	01	Irish Concrete Safety L...	Open	Safety	General Safety Inspecti...
011	01	Irish Concrete - Safety	Open	Safety	Detailed Safety Inspecti...
012	01		Open	Deliveries	Plumbing Fixtures
013	01	Trimble Fireproofing	Open	QA/QC	Fireproofing Checklist
014	01	Sectio 1235	Open	Deliveries	Plumbing Fixtures
015	01	Irish Concrete	Open	Safety	Detailed Safety Inspecti...

My Assignments

- Assigned to Me
- Assigned to My Company

Status

- Draft
- Open
- Pending Approval
- Rejected
- Approved
- Closed

Location

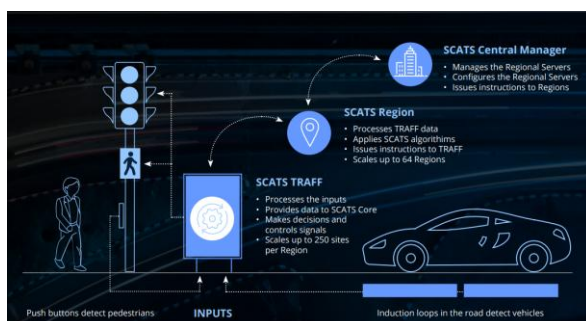
By

- Assigned To Contact
- Assigned To Company
- CCed To Contact
- CCed To Company

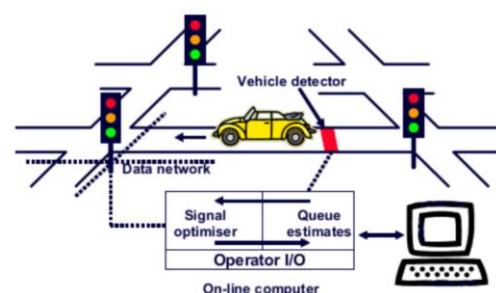
Figure B.21: AI optimises road construction and maintenance by improving planning, scheduling, and resource allocation through predictive algorithms and real-time analysis (Trimble ProjectSight, 2024).

9.1.7. Road operations, traffic, and incident management

The Sydney Coordinated Adaptive Traffic System (SCATS) is a notable advanced system developed to optimise traffic flow and reduce congestion. It uses real-time data from traffic sensors to adapt signal timings dynamically, enhancing efficiency across multiple intersections (SCATS, 2024). Adaptive signal control systems, such as SCATS, rely on enabling technologies that include advanced sensing components, specialised signal control equipment, and communications infrastructure such as optical fibre networks. These components ensure the accurate collection, transmission, and processing of data required for dynamic signal adjustments. SCATS adjusts signal patterns based on traffic demand, which helps alleviate bottlenecks and improve overall road safety. Originally implemented in Sydney, it has since been adopted globally (installed at about 55,000 intersections in over 180 cities in 28 countries), demonstrating its effectiveness in managing urban traffic networks and contributing to reduced travel times and environmental impact. It mainly uses complex mathematical models for optimisation tasks.



(a)



(b)

Figure B.22: (a) SCATS optimises signal timings using real-time sensor data, reducing congestion, enhancing safety, and minimising environmental impact (SCATS, 2024). (b) SCOOT adjusts signals in real time to improve flow, cut delays, and prioritise public transport.

Another well known real time adaptive traffic control system is the so-called Split Cycle Offset Optimisation Technique or SCOOT (SCOOT, 2024). SCOOT is an advanced adaptive traffic signal control system designed to improve the efficiency of urban traffic networks.

It uses real-time data from vehicle detectors to dynamically adjust traffic signal timings, ensuring smoother traffic flow and reducing delays. The system continuously responds to changes in traffic patterns without being overly reactive, avoiding large fluctuations in signal control. SCOOT also offers features such as customised congestion management, public transport and pedestrian priority, and vehicle emissions estimation, making it a comprehensive tool for modern traffic management. SCOOT is currently used in over 350 towns and cities globally.

Although the previous systems, i.e. SCATS and SCOOT, do not utilise the sophisticated AI-driven algorithms to automate the processes, the literature indicated active academic work towards this direction. For example, Li et al. (2020) have developed an advanced adaptive traffic signal control model using deep reinforcement learning, integrated within the Simulation of Urban Mobility traffic micro simulator. Their proposed model is able to determine the optimal signal phase and duration to minimise vehicles' waiting times, by using real-time traffic data, such as the number of vehicles and average speed at one or more intersections. Similar research works include e.g. Sun et al. (2022), Bálint et al. (2022), Jin et al. (2015) who have utilised AI-driven algorithms in adaptive traffic signal control. Apart from the academic works, NoTraffic is a leading AI-powered traffic signal platform. It uses AI to analyse real-time traffic data collected from various sensors and cameras placed at intersections. The AI algorithms assess factors such as traffic volume, vehicle types, and pedestrian movement to determine the optimal signal phase for each direction. Additionally, NoTraffic integrates with other traffic management systems and can respond to changing conditions, such as accidents or roadworks, to adapt traffic signals accordingly.

Kapsch TrafficCom's urban traffic management is another notable dynamic traffic and incident management system (Kapsch TrafficCom, 2024a). Similar to the other platforms, it uses real-time and predictive analytics, driven by AI, to manage traffic flow and control systems such as traffic lights and road signs. The AI system can also optimise traffic light timing, suggest alternative routes to drivers and prioritises public transport. It should also be highlighted that Kapsch TrafficCom has also contributed to the transport mobility of several cities globally including HICs and LMICs such as U.S., Panama, Ecuador, Colombia, Brazil, Argentina, Lebanon etc (Kapsch TrafficCom, 2024b). The concept of Kapsch intelligent corridor is shown in Figure B.23.

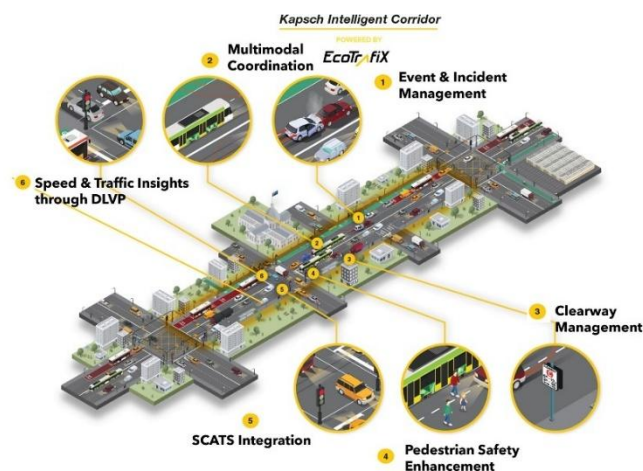


Figure B.23: Kapsch TrafficCom's AI-driven system optimises flow, controls signals, suggests routes, and prioritises public transport globally (Kapsch TrafficCom, 2024a & 2024b).

Another example of an advanced traffic management system which enables automated traffic management is the Network Intelligence & Management System (NIMS) used in Ireland's enhancing Motorway Operation Services (eMOS) project. This new system harnesses real-time data from multiple sources such as CCTV cameras, inductance loops, ANPR cameras etc. to dynamically determine speed and signal settings on the M50 motorway. This system, which is one of many similar systems globally, processes vast amounts of information, and can utilise ML or other automated algorithms to predict traffic flows and journey times, detect incidents, and identify congestion patterns. NIMS also enhances road safety and efficiency, by optimising traffic signal timings, providing accurate real-time updates to drivers, and coordinating incident response. Its proactive approach ensures smooth traffic flow and timely interventions, minimising disruptions and improving overall motorway operations. Figure B.24 briefly presents the eMOS concept.



Figure B.24: NIMS in Ireland uses real-time data from multiple sources for dynamic traffic management on the M50 motorway (eMOS, 2024).

The majority of traffic management systems presented earlier utilise advanced sensors to monitor and analyse traffic conditions. Although these sensor technologies do not necessarily use AI technology to operate, the data they collect can be utilised to enable AI-driven algorithms and perform future predictions, such as traffic flows. For example, commercially available radar and infrared technologies can be used to detect vehicle movement, speed, and volume at various points

on the road. This data is then processed using AI to provide real-time insights into traffic flow and detect incidents. Figure B.25 demonstrates this sensor technology.



Figure B.25: Radar and infrared sensors monitor traffic, while AI analyses data for real-time insights, optimising road management and incident response (Wavetronix SmartSensor Matrix, 2024).

Mico et al. (2023) have provided a comprehensive review of Internet of Things (IoT) sensor systems used for monitoring road infrastructure. Although the literature review in this research cannot cover all road infrastructure sensors, Figure B.26 shows some key examples of sensors identified in the literature which use image processing for traffic and incident response management.

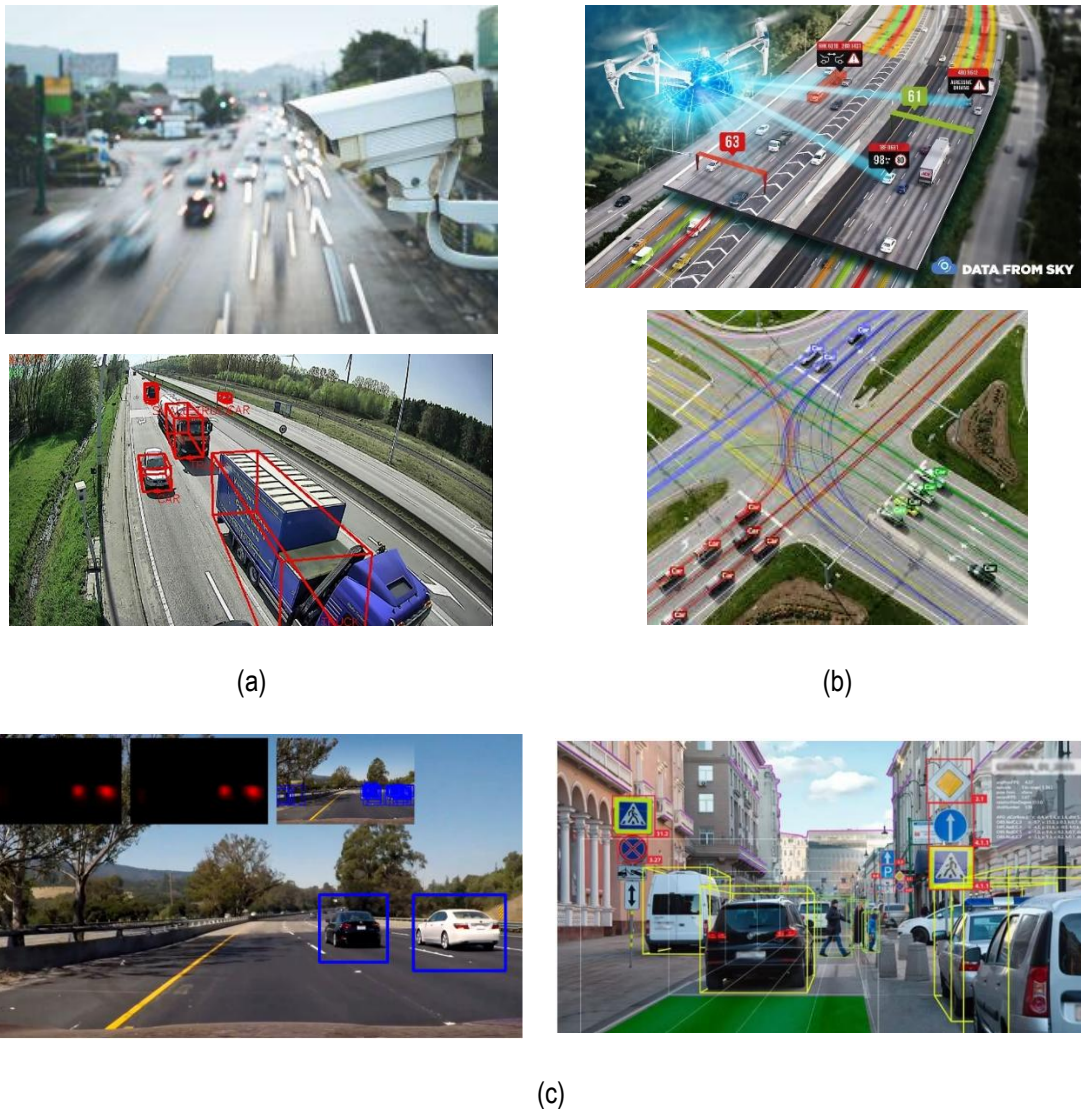


Figure B.26: AI-integrated traffic cameras monitor roads via (a) traditional surveillance (Universeoptics, 2024; TrifiCam AI, 2024), (b) drone-based systems (DataFromSky, 2024; Elistair, 2024), and (c) computer vision for vehicle surveillance (Labellerr, 2024).

The main AI technology used with these sensors is computer vision which analyses video from roadside or in-vehicle cameras and detects irregularities - such as sudden stops or collisions - and automatically alerts traffic management centres. This rapid detection facilitates quicker responses from emergency services and enables more efficient traffic flow management, ultimately improving road safety and reducing congestion. The research of this work noted that these systems have reached a reasonable level of maturity and it has been globally applied in various road infrastructures.

Alternatively incident response sensors use thermal imaging technologies. These employ advanced infrared cameras to detect and monitor heat patterns from vehicles and road conditions. These cameras capture the thermal signatures emitted by vehicles and infrastructure, even in low visibility conditions. Then, the collected data is processed using AI algorithms to identify and classify traffic flow, detect anomalies such as stalled vehicles, and monitor road surface temperatures. Figure B.27 illustrates examples of these technology.

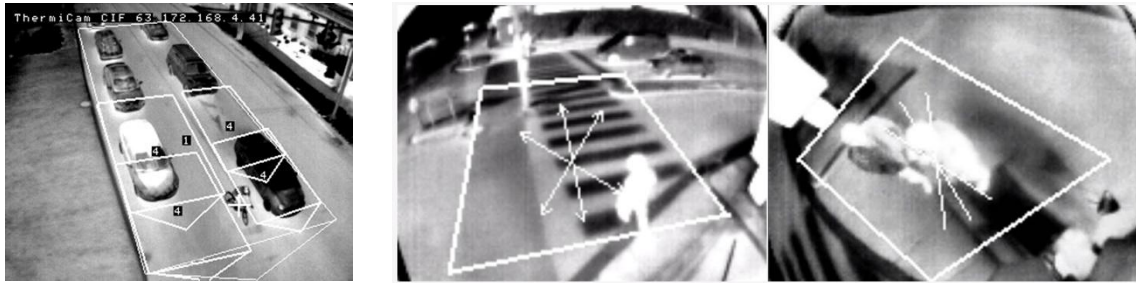


Figure B.27: Incident response sensors use thermal imaging and AI to detect heat patterns, identify traffic flow, and monitor road conditions (FLIR ThermiCam, 2024).

The literature review also identified AI-driven algorithms which are used to optimise public transport systems. One such example is depicted in Figure B.28 through the Optibus platform. This technology operates by analysing vast datasets to enhance route planning, schedule adherence, and resource allocation for public transport. It can predict demand patterns, dynamically adjust bus schedules, and allocate vehicles efficiently, thus minimising delays and operational costs. The system also enables precise forecasting and adaptive management by integrating real-time data and historical trends. Although these types of systems were not commonly found in the literature, they are already on the market, and their results are evident.



Figure B.28: Advanced AI technology enhances road operations by using ML to optimise route planning, scheduling, and resource allocation, reducing delays and operational costs (Optibus, 2024).

9.1.8. Tolling

Numerous examples of AI technology are evident in tolling activities. A prominent application involves using high-resolution cameras and advanced image recognition algorithms to capture and analyse vehicle licence plates in real time. This approach enables precise toll calculations and reduces manual intervention by dynamically adapting to various conditions, thereby enhancing efficiency and accuracy in toll collection.

Research indicates that AI-driven computer vision algorithms significantly enhance tolling operations through ANPR systems. These systems use sophisticated image recognition and ML algorithms to process high-resolution images of vehicle registration plates as they pass through toll

points. ANPR technology applies pattern recognition and data analysis to ensure accurate billing and minimise errors. It adjusts to varying lighting conditions and different plate designs, maintaining high accuracy across diverse scenarios. This innovation supports barrier-free tolling, which is now widespread globally. Additionally, it streamlines toll collection, improves operational efficiency, and reduces the need for manual intervention by eliminating physical toll booths and mitigating congestion. Figure B.29 presents a comparison between traditional barrier toll systems and AI-driven ANPR systems. Both systems are available, although barrier-free tolling systems are relatively new to the market.



(a)



(b)

Figure B.29: (a) Traditional barrier toll system (Google Maps). (b) AI-driven ANPR improves efficiency, enabling barrier-free tolling (Q-Free Intrada Insight, 2024)

To this extent, Chavan et al. (2021) have demonstrated how a vehicle detection and recognition system works through the diagram showed in Figure B.30. In particular, the number plate detection and recognition system automates toll collection by identifying vehicle registration plates, extracting characters, and verifying ownership details. It begins by capturing the vehicle's image and preprocessing it using techniques such as noise reduction, sharpening, and histogram equalisation to enhance quality.

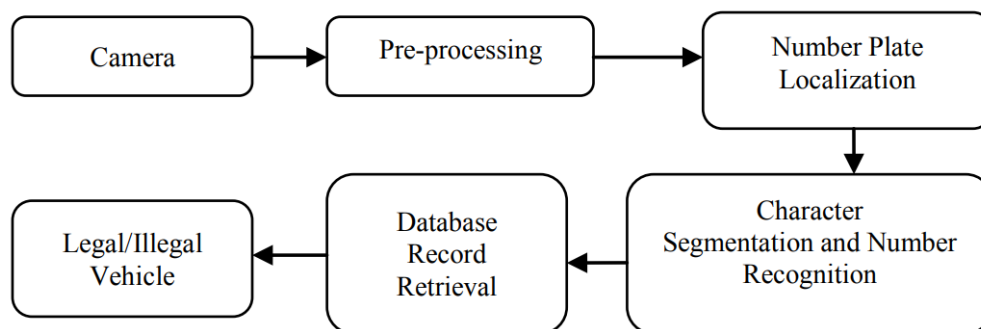


Figure B.30: Automated toll system captures number plates, recognises characters, and verifies vehicle details via NN and transport office database (Chavan et al., 2021).

Next, binarisation and edge extraction are applied to locate the number plate, followed by character segmentation to separate the alphanumeric characters. These characters are recognised using a Neural Network (NN) algorithm and cross-referenced with the regional transport office database for authentication. Legal vehicles are charged electronically, while unauthorised vehicles trigger alerts to the relevant authorities for further action.

Chavan et al. (2021) have also demonstrated the character segmentation and identification process which is outlined in Figure B.31.

The literature review has indicated a wide range of methodologies proposed for vehicle plate recognition across HICs and LMICs. Notably, Chavan et al. (2021) developed the system applied in India, while Arrieta-Rodríguez et al. (2019) proposed a web-based licence plate identification and recognition system in Colombia. In Bangladesh, Azam et al. (2016) explored number plate detection using images with environmental distortions such as rain, fog, low illumination, and contrast, as well as tilted number plates, experimenting with 850 car images. Additionally, Xie et al. (2018) introduced a real-time car licence plate detection system in Guangzhou, China, addressing rotational inaccuracies using a Convolutional Neural Network (CNN)-based framework. In HICs, vehicle plate recognition technologies emerged earlier, with e.g. Anagnostopoulos et al. (2006) applying plate character recognition through two-layer probabilistic NNs in Greece. This diverse body of work highlights the global development of vehicle plate recognition systems, tailored to varying local conditions and challenges.



Figure B.31: (a) region of interest, (b) number of plate extraction, (c) character segmentation, (d) license plate recognition (Chavan et al., 2021).

9.1.9. Winter services

The AI technologies identified in this research related to winter services and management include autonomous snowplough robots, road surface ice detection, and the efficient management of snow removal operations.



Figure B.32: AI-powered autonomous snowploughs use sensors, ML, and real-time data to map, detect obstacles, and optimise clearing, improving winter road safety (University of Minnesota Robotics, 2024).

Initially, autonomous snowploughs operate by integrating advanced sensors, machine learning algorithms, and real-time data processing. These snowploughs utilise LiDAR and cameras to map

their surroundings and detect obstacles, ensuring efficient snow clearing. The AI systems that are equipped with, analyse weather patterns and road conditions to optimise ploughing routes and techniques. This technology enables the autonomous vehicles to navigate complex environments, reducing human intervention and improving safety and effectiveness in snow removal operations. Figure B.32 illustrates an autonomous snowplough which was developed by University of Minnesota in the U.S. as part of a University competition. However, the literature review revealed that development of autonomous snowplough are a subject of active research and various academic-based systems have been tested such as Suer et al. (2023) who developed an autonomous robotic snowplough for residential use.

Very recently, private parties took the initiative to introduce the first remote-operated and autonomous industrial snow plough in the US market. Teleo, in partnership with Storm Equipment, introduced this technology (Teleo and Storm Equipment, 2024). Retrofitted onto any heavy machinery, it enables operators to control multiple machines from a central location, increasing efficiency and reducing staffing challenges in large-scale snow removal operations. Although this technology does not explicitly utilise AI, it marks the first step in the transition from traditional approaches to remote monitoring and automation in snow removal.

Literature review findings indicate that image-based technologies can also be applied in winter services and management. For example, the use of a polarisation camera in conjunction with AI algorithms are able to discern road surface conditions by analysing the light reflected off it, as illustrated in Figure B.33. The novelty of this technology, unlike conventional methods that rely solely on colour or brightness, is that the polarisation camera reveals detailed surface characteristics, such as ice patches that are otherwise invisible. The system integrates this data with deep learning algorithms to identify abnormal conditions indicative of ice, even if these conditions have not been pre-programmed. This approach ensures that real-time detection is accurate and adaptive, significantly improving the ability to manage and respond to winter road hazards. The research highlighted a good level of maturity of this technology and there are numerous research works which attempt to improve its accuracy under various environmental conditions such as Blin et al. (2019) for object detection in road scenes amongst many.

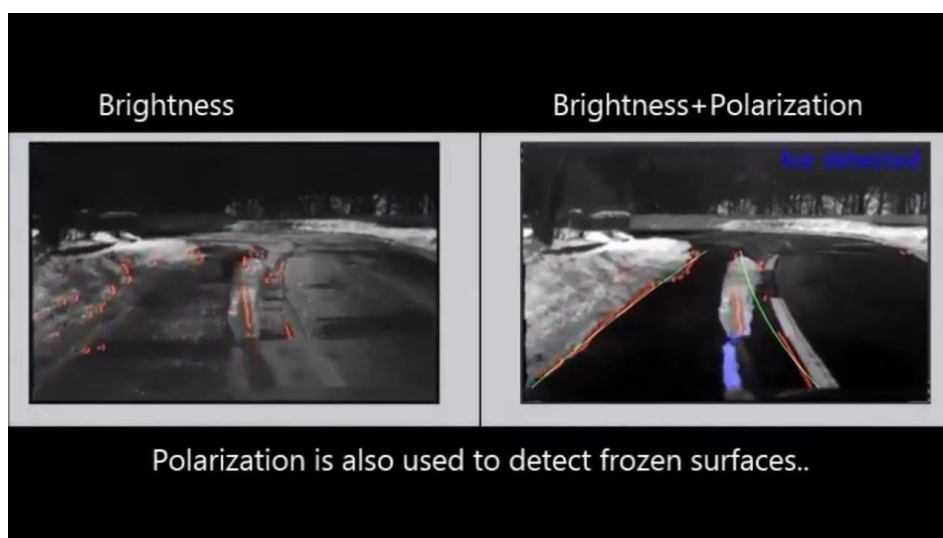
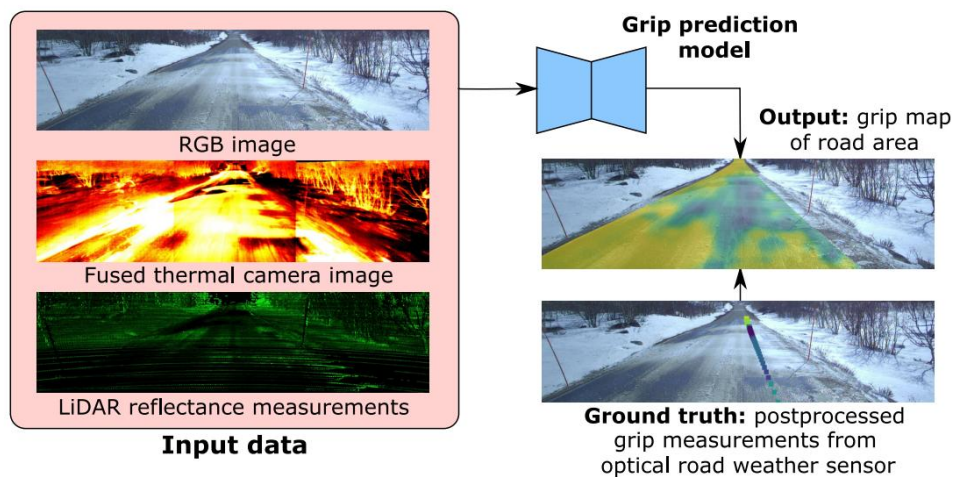


Figure B.33: This technology uses a polarisation camera and deep learning to detect road conditions, e.g. hidden ice, for real-time winter hazard detection (Ricoh, 2024).

An alternative image processing technology, utilising RGB and thermal camera images alongside LiDAR reflectance data, exists and is used to tackle the challenge of detecting slippery road conditions. Maanpää et al. (2024) have recently proposed such a system, and although its original concept is intended for autonomous vehicles, the same approach can be applied to conventional vehicles (see Figure B.34). The system employs convolutional NNs in conjunction with cameras to enhance detection capabilities and it is currently under development and academic stage.



(a)



(b)

Figure B.34: Slippery road detection system (Maanpää et al., 2024): (a) Data collected via research vehicle using (1) LiDAR, (2) RGB, and (3) thermal cameras. (b) CNN trained on optical road weather sensor data.

Roadside units can also be utilised to monitor road slipperiness. For example, Grabowski et al. (2020) proposed a system in Poland that employs CCTV cameras in conjunction with convolutional NNs. This system is capable of classifying road conditions as dry, wet, or snowy, with an accuracy of up to 98%. Although this approach only provides information on the road conditions - such as whether it is dry, wet, or snowy - rather than, for example, the friction coefficient of the asphalt

surface, this data can be integrated into traffic signage to enforce measures that help prevent vehicle skidding.

The last technology which was identified in the literature related to the management of winter hazards such as ice formation and snow accumulation. This technology is based on advanced ML algorithms which are able to process vast amounts of data from various sources, such as weather forecasts, traffic cameras, and sensors in the road infrastructure to accurately predict and detect hazardous winter conditions. This enables timely deployment of resources such as salt spreaders and snowploughs, optimising road safety and operational efficiency. In addition, the system can be dynamically adapted and improved over time, offering increasingly precise recommendations for winter road maintenance. Such systems have been reported in Salim et al., (2002), Attentive, (2024) and Pooya (2023) for snow and ice management amongst many (see Figure B.35).

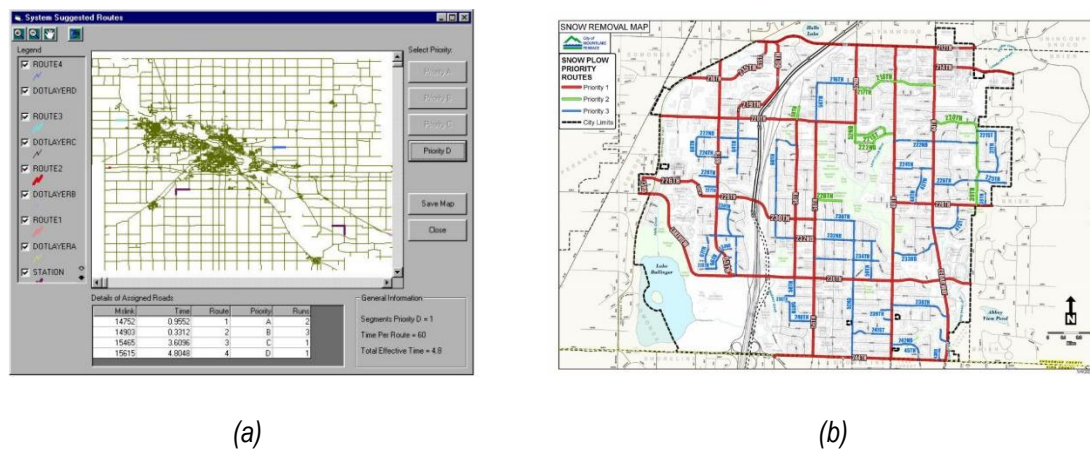


Figure B.35: (a) AI optimises snow removal management (Salim et al., 2002), (b) ML and computer vision monitor roads, predict hazards, and optimise resources for winter safety (Attentive, 2024).

9.1.10. Road safety

Enhancing road safety is one of the most critical concerns for road authorities, operators, and users alike. The application of AI in road safety has been evident since the early stages of its development. These systems primarily utilise camera-based image processing for data collection, which enables advanced AI algorithms, particularly computer vision, to proactively create safer road conditions for users. However, road safety can also be indirectly enhanced through the application of AI technology during the planning and feasibility stage, the design stage, and the operation stage. This section briefly describes AI technologies which were not addressed in the previous sections.

Model Name	Description	Type of Image	Classes
delineation	Adequacy of road lines	Frontal	2
street lighting	Presence of street lighting	Frontal	2
carriageway	Carriageway label for section	Frontal	2
service road	Presence of a service road	Frontal	2
road condition	Condition of the road surface	Frontal	3
skid resistance	Skidding resistance	Frontal	3
upgrade cost	Influence surroundings on cost of major works	Frontal	3
speed management	Presence of features to reduce operating speed	Frontal	3
bicycle facility	Presence of facilities for bicyclists	Frontal	2
quality of curve	Influence surroundings on cost of major works	Frontal	2
vehicle parking	Influence surroundings on cost of major works	Frontal	2
property access points	Influence surroundings on cost of major works	Frontal	2
area_type	Influence surroundings on cost of major works	Lateral	2
land use	Influence surroundings on cost of major works	Lateral	4
number of lanes	Influence surroundings on cost of major works	Frontal	5



(a)

(b)

Figure B.36: AI improves road safety with digital tools and iRAP Star Rating, reducing human error and enhancing interventions. (a) Road classification. (b) ML-processed images (ViaSegura, 2024).

One key technology employed in the road sector involves analysing images of road sections and classifying their attributes. For instance, ViaSegura in Brazil has utilised the International Road Assessment Programme (iRAP) Star Rating methodology - a globally recognised standard for evaluating road safety - to assess risks associated with each road attribute. Based on this analysis, critical or high-risk road sections are identified, and specific focus is given to these areas or proposed mitigation measures are developed. This technology uses computer vision to analyse and classify road attributes, significantly reducing the need for human intervention and minimising errors in data processing. However, the system's effectiveness is highly dependent on the quality and consistency of data across regions to ensure reliable assessments and interventions. An example of the ViaSegura algorithm is shown in Figure B.36. Further details of ViaSegura implementation are elaborated in Section 4.2.

A key technology extensively discussed in the literature is ADAS, which enhance vehicle safety through real-time environmental monitoring. These systems employ computer vision and a range of in-vehicle sensors, such as radar and cameras, to continuously scan the road ahead. The data collected is processed through AI-driven algorithms, integrating multiple sensor inputs to detect pedestrians, traffic signs, and lane markings with high accuracy. As the vehicle navigates, these intelligent algorithms predict the movements of surrounding vehicles and dynamically adjust the vehicle's trajectory. The system provides drivers with timely alerts and automated interventions, significantly reducing the risk of accidents. A practical application of ADAS is illustrated in Figure B.37, which presents a case study from Nagpur city buses in India, demonstrating the critical role of early driver alerts, particularly those issued two seconds before potential hazards.

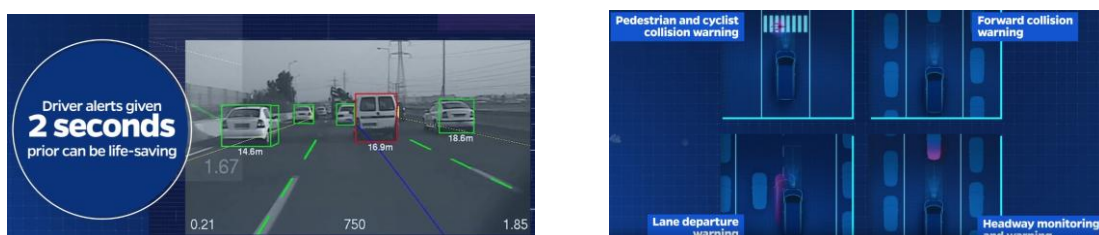


Figure B.37: ADAS vehicles use AI-driven vision, radar, and cameras to detect hazards, predict behaviour, and issue alerts, enhancing safety and reducing accidents (iRASTE, 2024).

Another camera-based technology that has achieved a high level of maturity is depicted in Figure B.38. This technology utilises AI-powered cameras to monitor vehicle interiors through windscreens, detecting drivers who are using mobile phones or failing to wear seatbelts. Computer vision algorithms analyse and identify these violations, generating evidence for legal enforcement.



Figure B.38: AI-powered cameras monitor vehicle interiors to detect mobile phone use and seatbelt violations, enhancing safety through compliance enforcement (Acusensus, 2024).

This approach aims to reduce distracted driving and ensure adherence to seatbelt regulations, thereby contributing to a decrease in road traffic accidents and enhancing overall road safety. Further details on this system are available in the case study in Section 5, which describes its use in New South Wales for enforcement of illegal mobile phone use while driving and seatbelt offences.

Similarly, there are in-vehicle systems which analyse data from different types of cameras, such as infrared and colour cameras. Then, data is integrated with computer vision algorithms which detect crucial issues for the driver e.g. drowsiness, distraction, and cell phone use, as well as identify smoking, all of which can impair driving. Please refer to Figure B.39 for an illustration of this technology. The information is processed in real-time and provides immediate alerts or interventions to help prevent accidents and enhance overall road safety. The use of AI in this context is essential for reducing human errors and ensuring safer driving conditions.



Figure B.39: AI enhances vehicle safety by monitoring driver behaviour in real time, detecting drowsiness, distraction, phone use, and smoking, issuing alerts to prevent crashes (Nota AI, 2024; Zhao et al., 2020).

Image processing technologies are also used for detecting motorcycle helmet as shown in Figure B.40. Those systems employ deep learning algorithms, such as CNNs, to analyse images from road surveillance cameras. The deep learning model is trained on vast datasets of helmeted and non-helmeted motorcyclists, enabling it to discern helmet use with high precision. This application of AI is key in monitoring and enforcing safety regulations within the road sector. The literature review indicated that this technology has a very good level of maturity and it has been applied globally including LMICs. For example, Siebert et al. (2020) have tested this technology to 7 cities across Myanmar.

A final AI-powered technology which is linked to alcohol concentration violation is shown in Figure B.41. This system, developed to estimate Blood Alcohol Concentration (BAC) through facial features, represents a significant advancement in road safety. It uses standard RGB cameras to analyse subtle physiological changes in a driver's face that indicate alcohol intoxication. Keshtkaran et al. (2024), who proposed this technology, claim it can predict BAC levels as low as 0.05 g/dL, aligning with legal thresholds for driving impairment. This enables real-time assessment of driver impairment, identifying intoxicated drivers before they engage in risky driving behaviour. The primary contribution of this technology is its potential to significantly reduce alcohol-related road accidents.

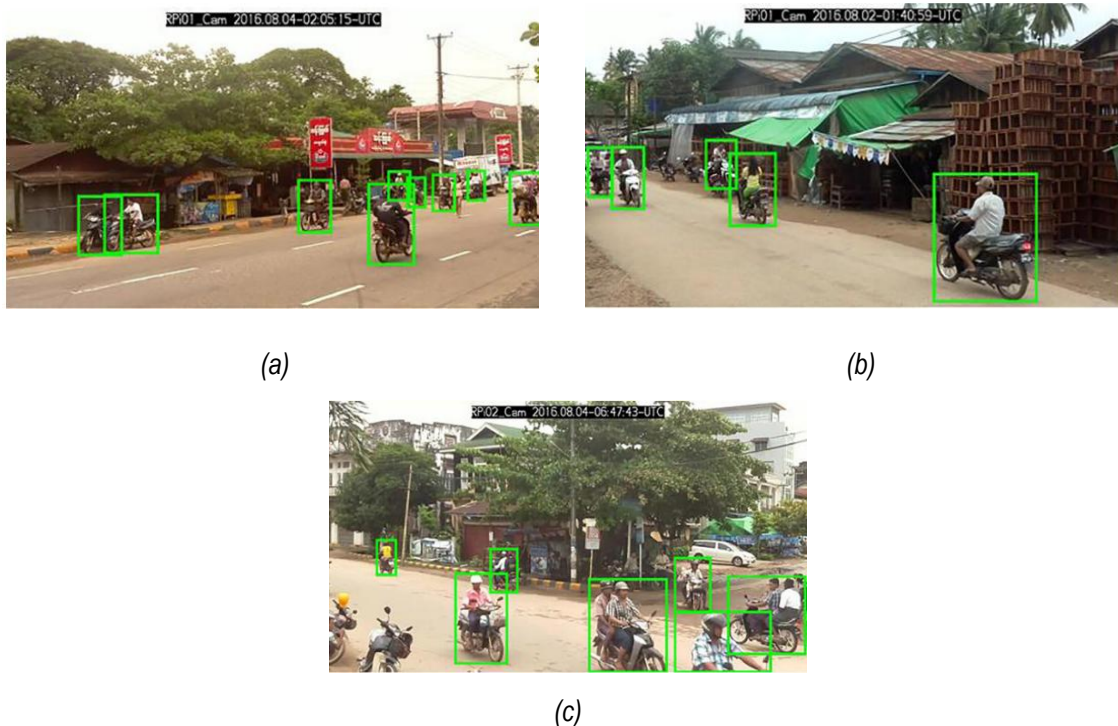


Figure B.40: AI improves road safety using deep learning and CNNs to detect helmet use, ensuring compliance and reducing injuries on (a) highways, (b) rural, and (c) urban roads (Siebert et al., 2020).

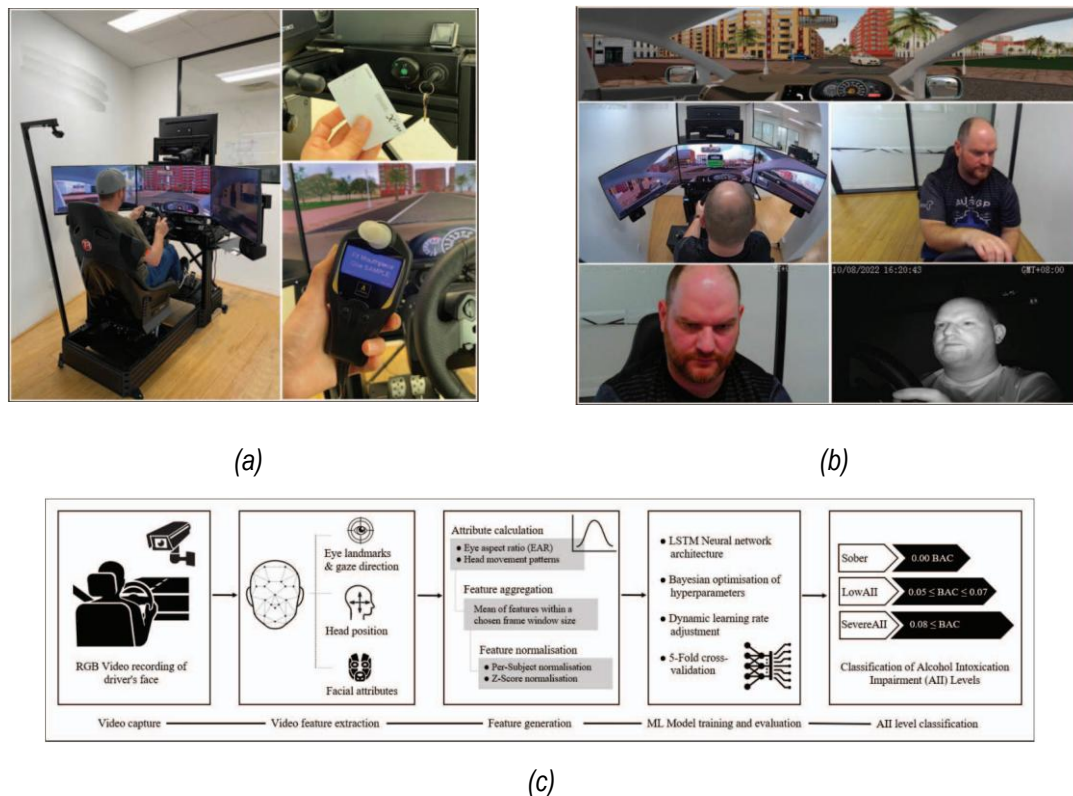


Figure B.41: AI estimates BAC via facial analysis with RGB cameras, assessing driver impairment in real time to enhance road safety (a) simulator with breathalyser and ID reader, (b) simulation setup with cameras, (c) AI workflow (Keshtkaran et al., 2024).

9.1.11. Asset management

The optimisation of asset management is a crucial task for road authorities across the world and utilising newly developed AI technologies can, in many cases, help improve this task. The use of computer vision along with AI predictive analytics can help in the assessment of entire road network. This can provide objective data-driven decision-making for road authorities when making decisions in relation to resource allocation. For example, Tableau commercial product serves as a powerful data visualisation tool, integrating diverse data sources to inform evidence-based funding allocation decisions, optimising public fund usage to align investments with community needs. This section explores a number of AI applications which have helped enhance road asset management.

The EU funded Omicron project is a complex system designed to improve asset management in the road sector by integrating digital inspection technologies with advanced AI. This technology utilises multiple robotic solutions, including drones and automated ground inspection vehicles, to perform precise and efficient road inspections. These drones, equipped with detect-and-avoid capabilities, create high-quality aerial images and 3D maps of road infrastructure, feeding this data into a comprehensive road DT. This digital representation of the road network allows AI algorithms to analyse the condition of assets such as pavement and road structures, enabling predictive maintenance and smart interventions. The system aims to improve road network availability and safety while reducing human exposure to traffic during inspections. Automation is to the fore in this Omicron project and a robotic modular platform will allow for autonomous operation for maintenance tasks in the future.

It is important to note that while AI has shown significant potential in replacing traditional visual inspections, challenges remain in detecting all types of damage. A hybrid approach, combining AI with conventional inspection methods, may offer a more robust solution during the transition phase, ensuring more comprehensive and reliable damage detection.

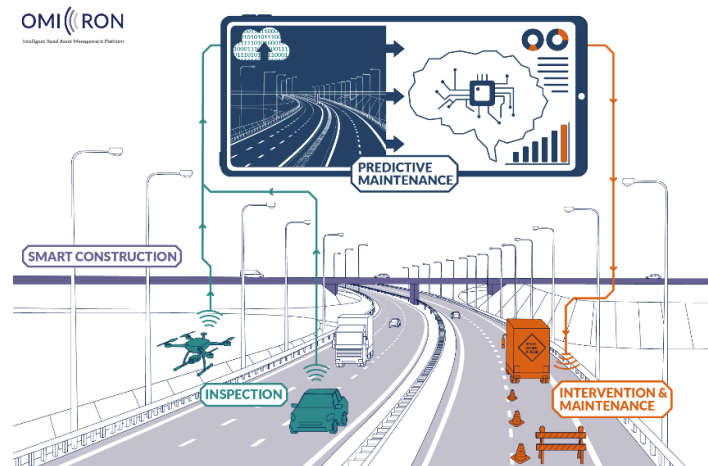


Figure B.42: The OMICRON project enhances road management with AI, integrating UAVs, inspections, robotic maintenance, and a DT with Decision Support for planning (Omicron Project, 2024).

StreetScan uses AI-driven mobile sensing technology to assess road conditions in real time, identifying defects and optimising maintenance planning for cost-effective infrastructure management.

A different AI technology classifies unpaved road conditions using high-resolution satellite imagery and ML algorithms. ML models analyse surface texture and wear patterns to predict current and future road conditions, supporting proactive asset management. This enables authorities to forecast maintenance, allocate resources efficiently, and schedule interventions. Particularly beneficial for LMICs, it provides cost-effective road assessments without expensive ground or aerial surveys. Further details are in Section 5, focusing on its development and application in African countries.

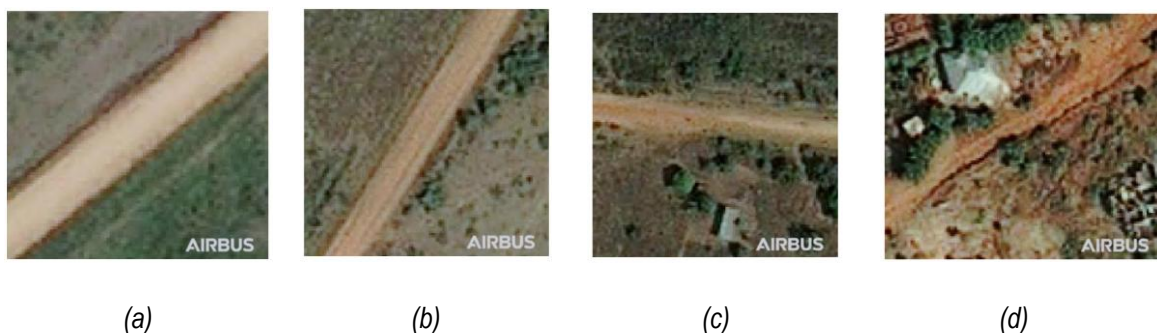


Figure B.43: AI with satellite imagery and ML predicts unpaved road conditions, optimising asset management and maintenance: (a) good, (b) fair, (c) poor, (d) bad (Workman et al., 2023)

9.1.12. Infrastructure inspection, monitoring, maintenance and repairs

Infrastructure inspection, monitoring, maintenance and repairs is one of the road activities with the most amount of AI applications due to the nature of the work. This activity, as evident in Figure

B.44, employs advanced AI technologies such as computer vision, AI predictive analytics software, drone-based remote sensing, LiDAR sensors and ML (data driven) algorithms along with numerous other technology types.

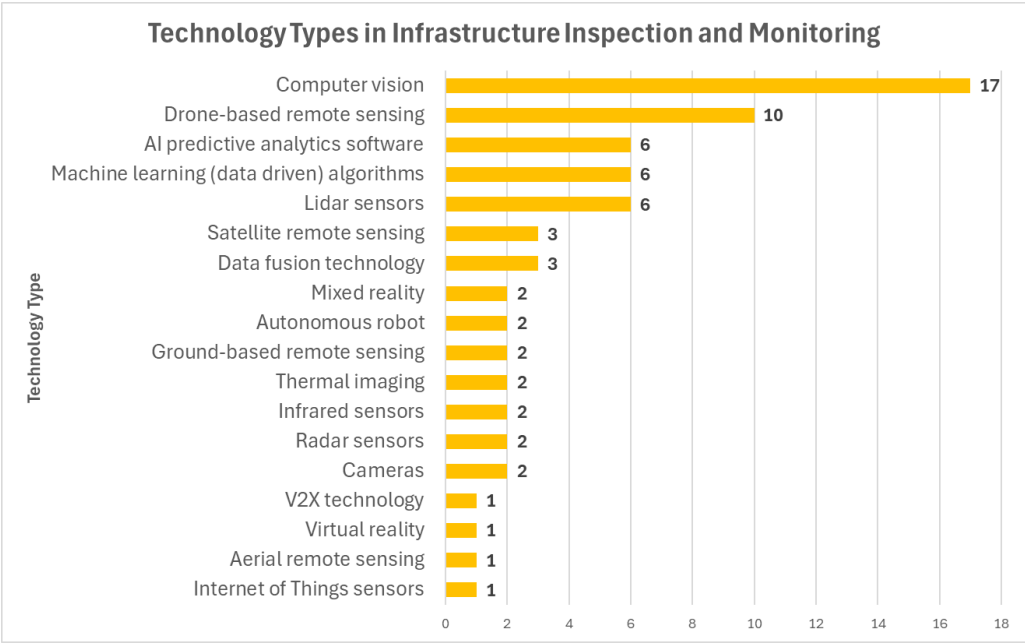


Figure B.44: Main AI technologies for inspection and monitoring in the literature review.

Computer vision and deep learning has been utilised to detect potholes, offering precise identification and classification of road surface anomalies. Also, the use of 3D reconstruction techniques enables the creation of accurate digital models of potholes, facilitating detailed mapping and assessment of road network defects. Additionally, autonomous robots, integrated with AI, are equipped to conduct real-time pothole repairs, enhancing road maintenance efficiency. All of which can be seen in Figure B.45.

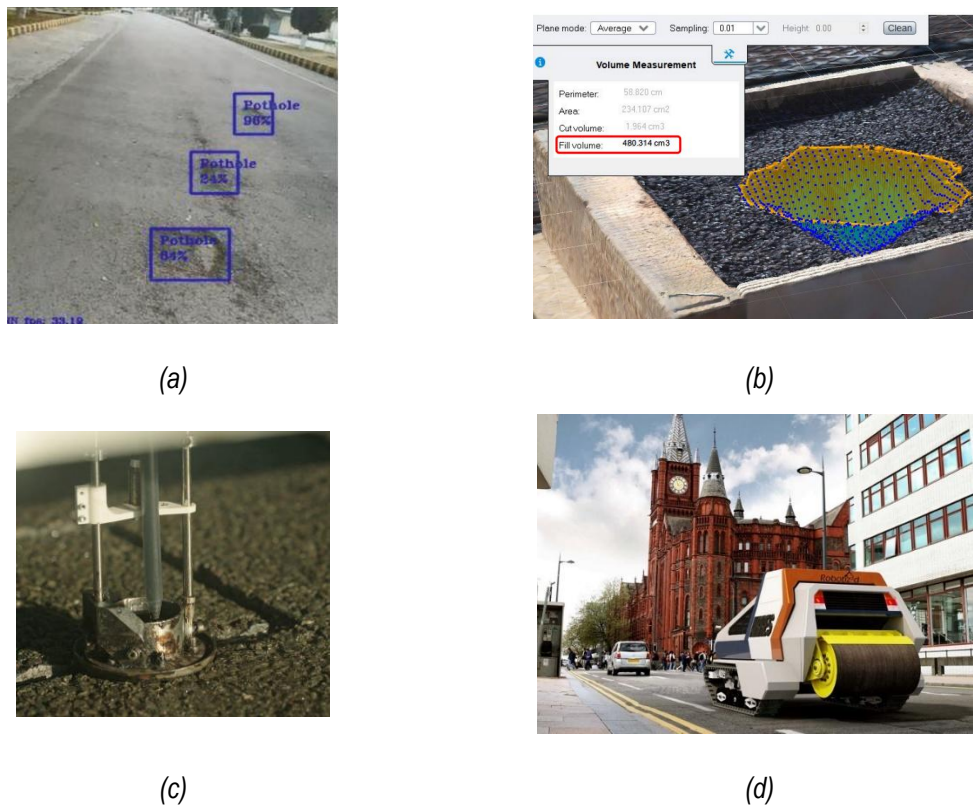


Figure B.45: Road inspection and repair: (a) pothole detection (Asad et al., 2022), (b) 3D mapping (Bruno et al., 2023), (c)(d) autonomous repair (Robotiz3d, 2024).

The INFRACOMS (Innovative and Future-proof Road Asset Condition Monitoring Systems) project, funded by the Conference of European Directors of Roads, analysed case studies showcasing the application of emerging technologies in asset management for NRAs. Rather than conducting original case studies, INFRACOMS reviewed and synthesised existing implementations of remote condition monitoring technologies by NRAs and other road authorities. The project aimed to extract insights from these applications to inform future practices and guide technology assessments. The case studies examined within INFRACOMS featured the following technologies.

INFRACOMS case study “EyeVi technology platform”. This platform enhanced decision-making in Oslo by providing objective, data-driven insights, addressing data gaps, and improving budget allocation. The AI-driven system, integrating 360° panoramic photography and LiDAR scanning, collected and processed extensive geospatial data across road networks, including surface conditions, traffic signs, road markings, and other assets. AI analysis enabled asset identification, condition assessment, and issue detection, facilitating the creation of comprehensive digital maps to support proactive maintenance and resource allocation, enhancing road longevity and safety. However, challenges such as delivery delays and difficulty in accurately assessing certain defects limited its effectiveness. See Figure B.46 for an illustration of this technology.

INFRACOMS case study “Aerial Satellite Spectroscopy (InSAR technology)”. It is used by Connect Plus Services on the M25 motorway, monitors ground movements by analysing satellite radar signals. AI-driven signal processing and ML algorithms detect and interpret subtle ground deformation patterns, identifying seasonal and climate-induced shifts crucial for infrastructure stability. The case study demonstrated InSAR’s versatility in monitoring geotechnical structures. See Figure B.55 for an illustration.



(a)



(b)



(c)

Figure B.46: AI improves road asset management through geospatial analysis, enabling proactive maintenance. (a) equipment, (b) AI registers traffic signs, (c) road damage visualisation (EyeVi, 2024).

INFRACOMS case study “COWI virtual inspection platform”. This platform was used for bridge reliability assessments, enabling virtual inspections to reduce the need for physical access. Tested for maintaining the Faroe bridges under the Danish Road Directorate, it provided a more efficient approach to monitoring conditions and identifying defects, minimising manual inspections. A key AI component is computer vision algorithms for damage detection, analysing high-resolution imagery to identify structural issues such as concrete cracking and spalling. AI further visualised vulnerable zones, including corrosion-prone areas, supporting proactive maintenance. See Figure B.47 for an illustration.

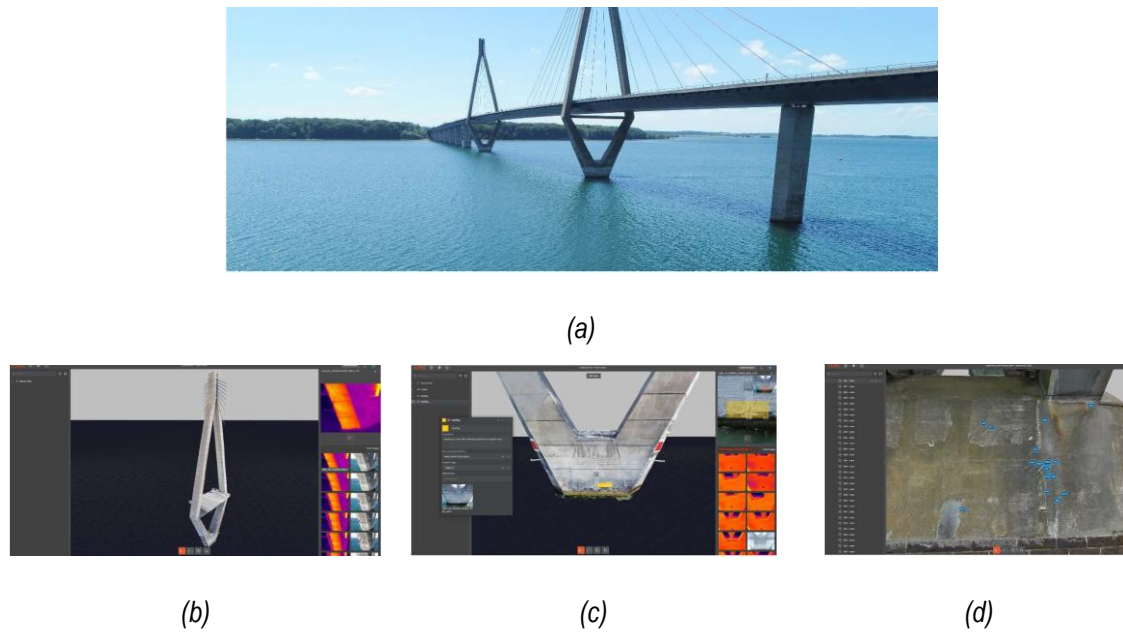


Figure B.47: (a) Faroe Bridges, cable-stayed; (b) North pylon in COWI Inspection; (c) corrosion zones; (d) AI-detected damage (Jensen J. et al., 2023; Fjendbo et al., 2023a).

INFRACOMS case study “Wireless acoustic emission technology”. This technology was used for real-time bridge reliability monitoring, providing data on structural health. Tested on a bridge managed by Rijkswaterstaat, the Dutch NRA, it demonstrated the ability to detect early stress signs, enabling timely maintenance and ensuring safety. The AI component utilises signal analysis through pattern recognition algorithms, processing acoustic signals from the UniQ wireless sensor node to identify patterns linked to crack formation or stress build-up. This data is integrated into a damage indication map to support informed decision-making. See Figure B.48 for an illustration.

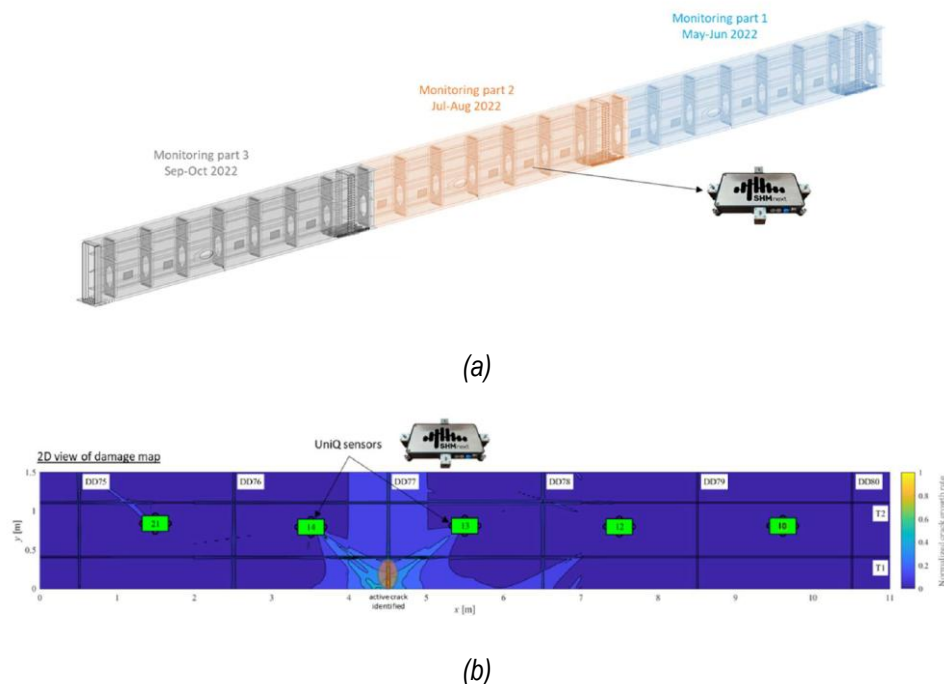


Figure B.48: Wireless acoustic emission technology (a) The simulated girder with three monitoring parts, (b) UniQ data processing results: the damage indication map (Fjendbo et al., 2023a).

INFRACOMS case study “Bridge weigh-in-motion technology”. It was used to assess bridge reliability on multi-span viaducts along the Ljubljana-Maribor highway. Although not AI-based, it enabled real-time data collection on vehicle weights, providing essential input for AI-driven analysis of load impacts on bridge structures. This data is fundamental for developing AI models that enhance maintenance planning and ensure structural safety. See Figure B.49 for an illustration.

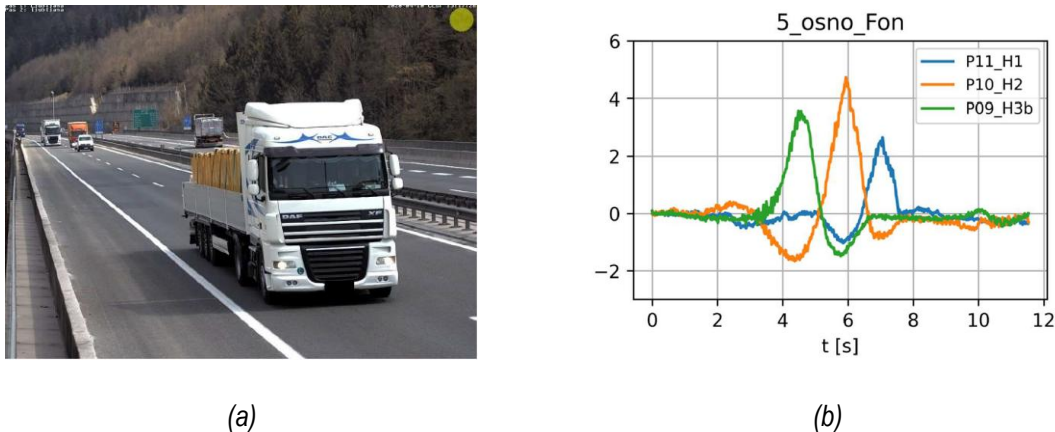


Figure B.49: Bending strain time history records bridge performance per calibration run: (a) Calibration vehicle; (b) Strain response (Hekič et al., 2022; Fjendbo et al., 2023a).

The INFRACOMS project identified key implementation challenges from the case studies. Deployment delays arose due to technical difficulties and organisational resistance. Some technologies faced data collection limitations, particularly for infrastructure components such as curb stones and storm drains. Additionally, staff resistance hindered adoption. Despite these obstacles, the case studies provided insights into implementation costs, helping NRAs evaluate the financial impact of advanced monitoring systems. Overall, despite these challenges, the technologies positively influenced asset management, enabling data-driven decision-making (Fjendbo et al., 2023b).

The use of UAVs for bridge damage inspection in the road sector integrates AI to improve precision and efficiency in infrastructure monitoring. Equipped with high-resolution cameras and sensors, UAVs capture detailed images and data from hard-to-reach bridge areas. AI algorithms analyse captured data to detect structural defects, such as cracks and material degradation, by identifying patterns and comparing them with historical data. This technology enables continuous, non-intrusive monitoring, ensuring early issue detection, timely maintenance, and bridge safety. As an emerging technology, it enhances inspection efficiency and is expected to improve further with wider adoption.

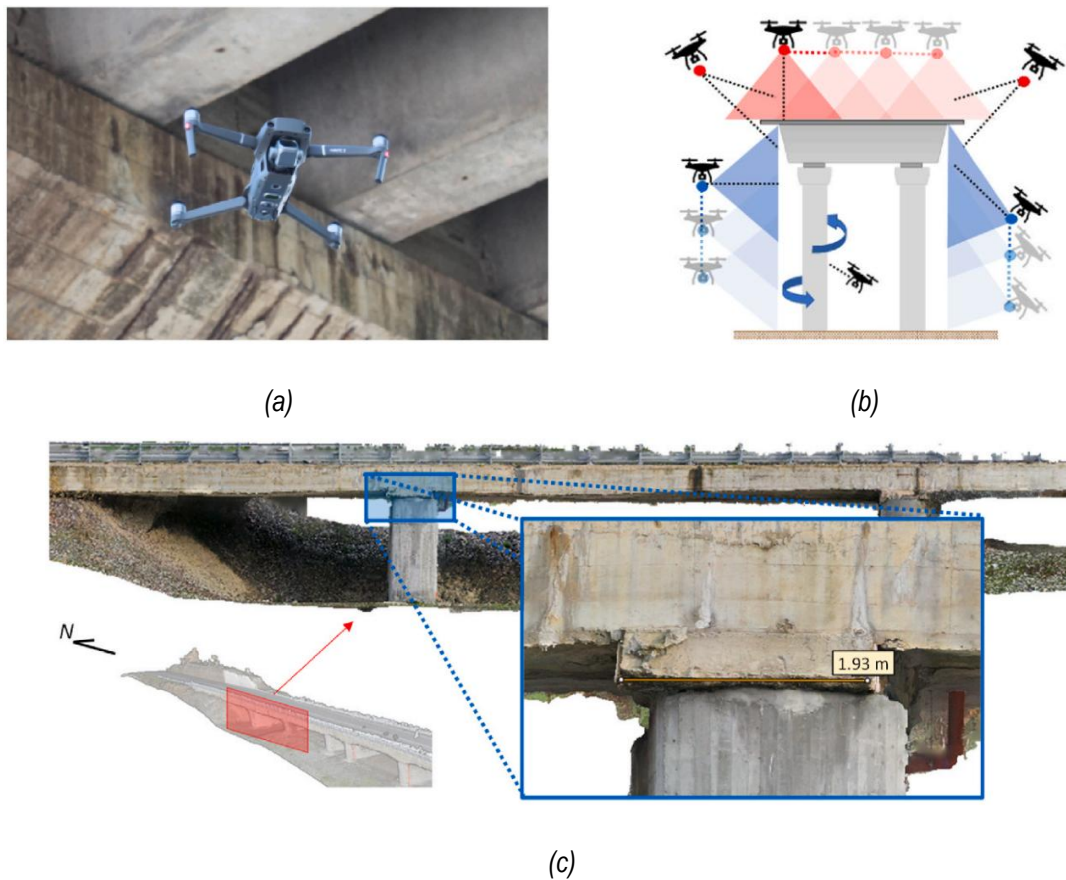


Figure B.50: "AI-UAVs aid bridge monitoring: (a) UAV inspection, (b) flight routes, (c) 3D AI inspection (Mandirola et al., 2022).

UAVs are also used for tunnel inspections, navigating confined spaces to capture detailed images and data. AI algorithms analyse this information to detect structural issues, such as cracks or water ingress, enabling early detection and timely maintenance to ensure tunnel safety and integrity. Please refer to Figure B.51.

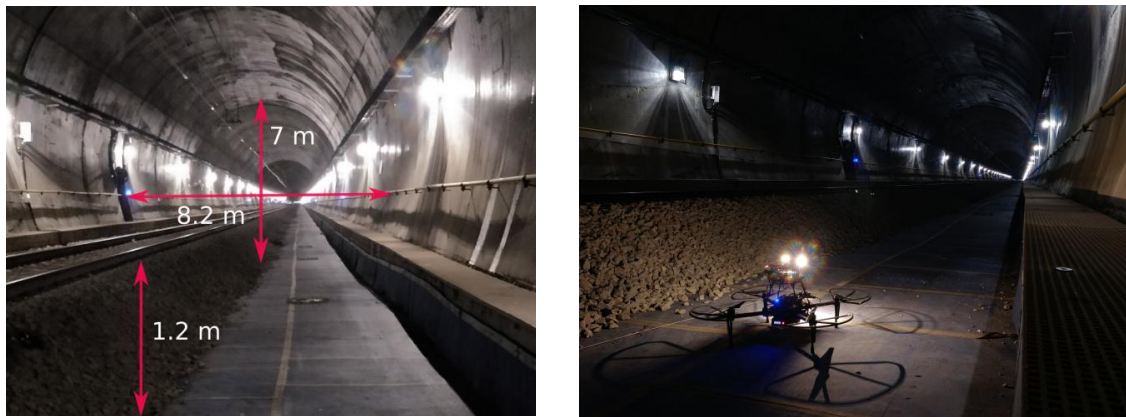


Figure B.51: UAS inspect tunnels by capturing detailed images in confined spaces and using AI to analyse data for early detection of structural issues, ensuring timely maintenance and safety (Bendris et al., 2022).

VR enhances infrastructure inspection efficiency by integrating UAV photogrammetry and LiDAR technology. The AI component employs ML algorithms to process large UAV and LiDAR datasets, enabling real-time rendering and pattern recognition for damage detection. For structural assessment, finite element analysis and operational modal analysis support SHM. This collaborative environment allows SHM data to be accessed remotely, enabling experts worldwide to virtually assess bridge conditions, as shown in Figure B.52 (Luleci et al., 2022).

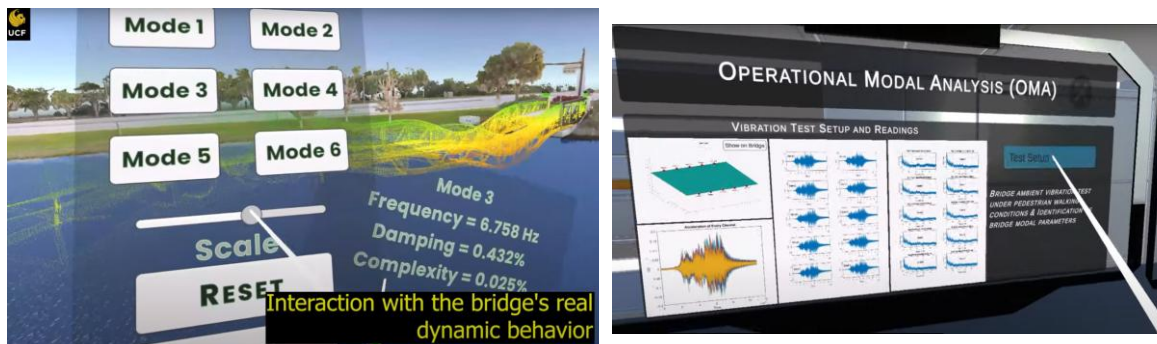


Figure B.52: VR environment for SHM of a foot bridge (Luleci et al., 2022).

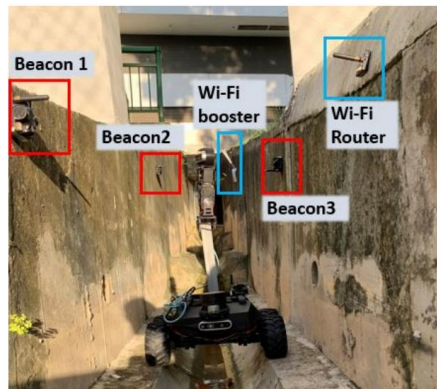
The autonomous robot for drainage and sewer inspection is a sophisticated AI-driven technology designed to enhance infrastructure inspection and monitoring in the road sector. This technology operates by navigating through underground drainage systems, using advanced sensors and AI algorithms to detect and analyse structural conditions. Equipped with cameras, LiDAR, and other sensing devices, the robot can identify blockages, cracks, or corrosion with high precision. The AI processes the gathered data in real-time, allowing for detailed mapping and assessment of the drainage infrastructure. This ensures early detection of potential issues, thereby supporting the maintenance and longevity of road systems.



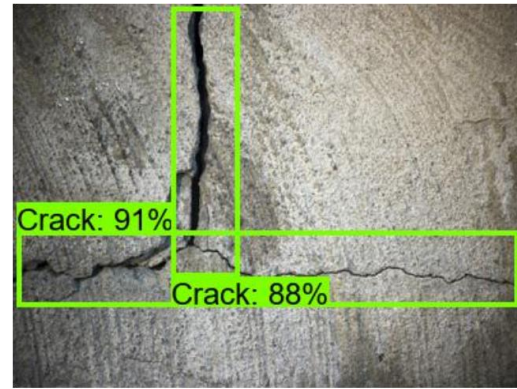
(a)



(b)



(c)



(d)

Figure B.53: AI-driven robot inspects drainage/sewers: (a) sewer inspection, (b) manhole entry (Grau et al., 2019), (c) drainage check, (d) AI defect detection (Palanisamy et al., 2021).

Indirect bridge monitoring, an emerging structural engineering approach, uses vehicle-mounted sensors to assess bridge conditions without on-structure equipment. This method analyses dynamic responses, such as natural frequency variations, mode shapes, and damping, as vehicles cross. AI algorithms interpret these interactions to detect structural issues and potential damage. Addressing limitations of traditional monitoring, it reduces installation costs and avoids operational disruptions. As a non-invasive, cost-effective solution, it is particularly suited for LMICs, where resource constraints limit direct monitoring feasibility.

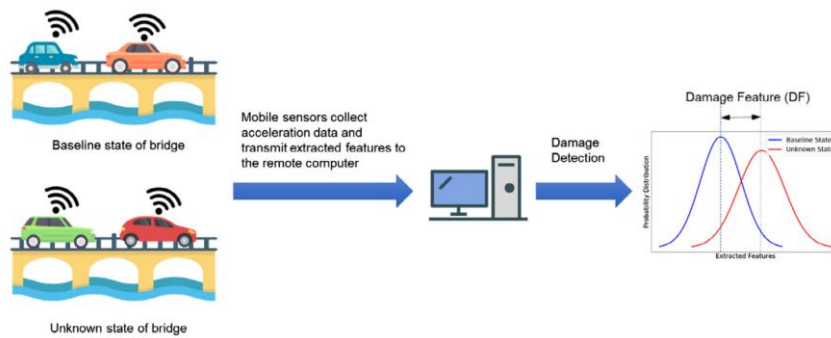
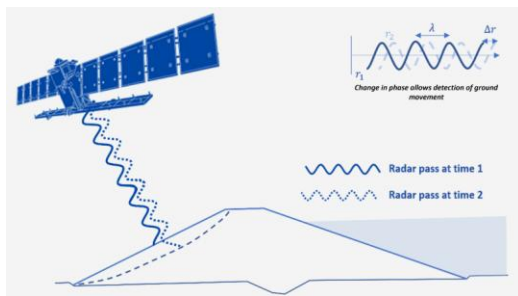
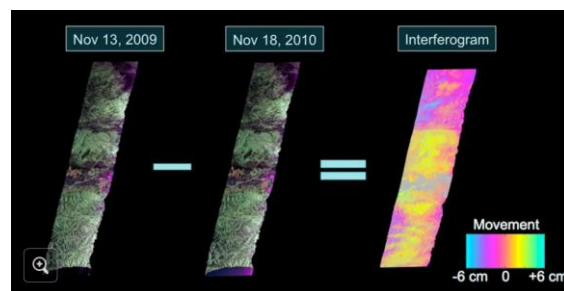


Figure B.54: Vehicle-mounted sensors assess bridge health via dynamic responses, providing a cost-effective, non-invasive alternative (Mei et al., 2019; Malekjafarian et al., 2015).

InSAR (Interferometric Synthetic Aperture Radar) detects ground movement by analysing radar images of the same area over time. It measures phase differences between satellite radar signals and ground reflections, with advanced algorithms identifying minute surface deformations. In infrastructure monitoring, InSAR assesses roadways and structures, detecting shifts or subsidence that indicate structural issues, enabling timely maintenance and failure prevention. AI integration enhances data processing efficiency, improving monitoring precision and speed (Bernardi et al., 2021).



(a)



(b)

Figure B.55: (a) InSAR tracks ground movement via satellite radar (SatSense, 2024); (b) San Andreas interferogram shows displacement (Nasar, 2024).

Air-quality sensors continuously monitor atmospheric conditions, detecting pollutants and using ML algorithms to predict trends and identify anomalies. AI-driven cameras assess vehicle emissions and fuel consumption, processing real-time data to ensure compliance with environmental standards. IoT-based noise sensors provide continuous acoustic pollution monitoring, offering insights into noise levels and infrastructure impact. Together, these technologies enhance the precision and efficiency of road infrastructure monitoring.

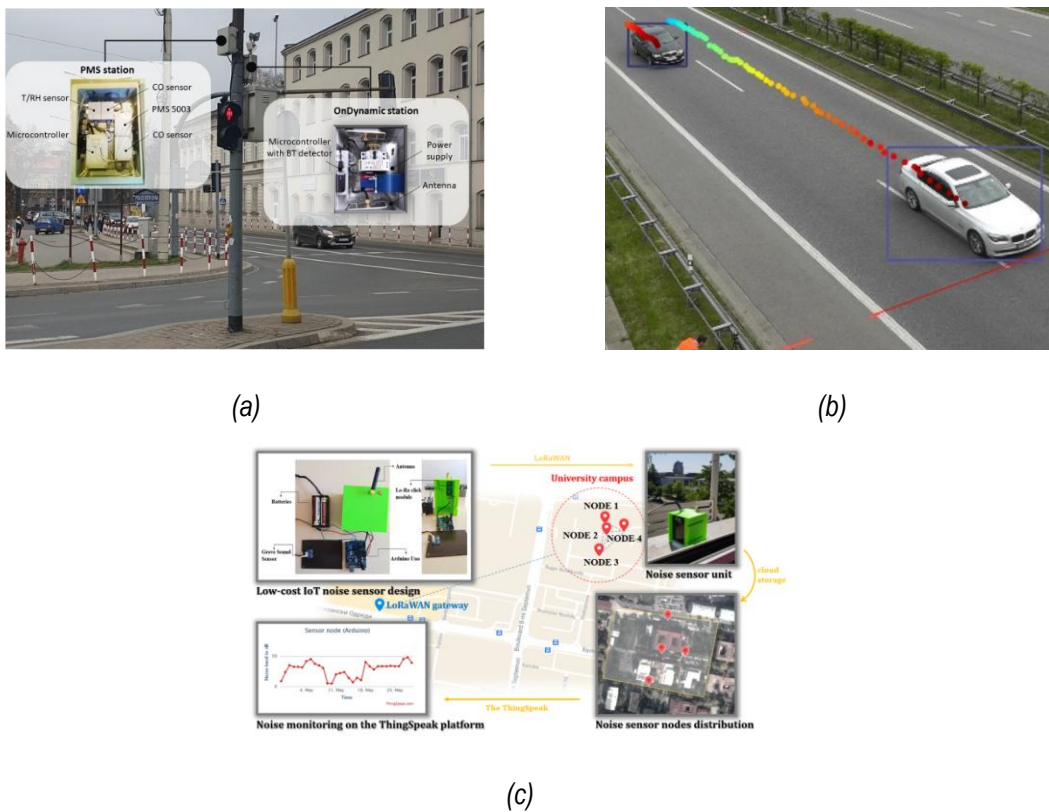


Figure B.56: Pollution monitoring: (a) air-quality sensors (Brzozowski et al., 2019), (b) AI-based vehicle emissions tracking (Valido et al., 2023), (c) IoT noise sensor (Anachkova et al., 2021).

9.1.13. Policy development

The literature reviewed in this study suggests that AI technologies employed in policy development are primarily AI-driven models designed to process large datasets, providing insights for policy professionals.

These systems are predominantly focused on improving road safety, analysing traffic-related data such as speed, weather conditions, vehicle density, and accident history to identify patterns associated with collisions. As a result, they are capable of predicting high-risk areas or conditions that may lead to accidents. Similar to the systems explored in this report within the context of traffic management, incident detection, and road safety, these AI-driven models can also propose safety interventions, including adjusting speed limits, installing traffic cameras, or enhancing lighting at specific intersections. The data-driven insights offered by these systems facilitate the creation of tailored safety policies, enabling governments to implement preventative measures precisely where and when they are most required, with the potential to significantly reduce the incidence of accidents. For example, Marceddu et al. (2024) explored how to enhance the road safety for vulnerable populations in Genoa, Italy, through AI-driven tools and data-informed policymaking. This enabled municipalities to effectively identify safety risks, prioritise improvements in pedestrian and cyclist routes.

9.1.14. Finance, funding, and procurement

The AI technologies within these road activities limited to AI-powered software. The most notable type is AI-driven cost estimation tools. For example, CostOS commercial product uses optimisation algorithms to provide cost estimation for construction projects and roadworks. It is enabled by

analysing historical data and generates detailed cost breakdowns to assist in budgeting and financial forecasting. A key benefit of this technology is that it avoids budget overruns and ensures that funds are allocated efficiently. Those software tools are very similar to the ones described for the construction and project management road activities, respectively.

Another construction management software, called Procore, streamlines procurement processes by evaluating supplier bids based on performance metrics and compliance, thereby enhancing transparency and reducing resource expenditure. In addition, Oracle's Risk Management Cloud employs AI algorithms to assess financial and operational risks by analysing economic indicators and historical project data, enabling stakeholders to anticipate potential financial pitfalls and improve strategic planning.

For enhanced financial transparency, IBM Blockchain facilitates the creation of smart contracts that automate payment processes, thereby reducing fraud risk and ensuring funds are disbursed according to project milestones. The AI component of IBM Blockchain lies in its use of ML algorithms to enhance fraud detection and improve the efficiency of payment verification processes. These algorithms analyse transactional data patterns to flag anomalies and potential risks, ensuring secure and reliable fund transfers. Lastly, Cubic Transportation Systems employs ML for revenue forecasting in toll collection, providing accurate predictions that aid in financial planning for future infrastructure projects. Collectively, these technologies foster more informed decision-making and efficient resource allocation within the road sector.

LEGISLATION AND GOVERNANCE

AI implementation in the road sector presents complex challenges, barriers, and risks, requiring robust legislative and governance frameworks to ensure safe and ethical deployment. The rapid advancement of AI has outpaced the development of comprehensive global regulations, though legislative progress is expected to align with ongoing technological advancements. Currently, the global regulatory landscape remains fragmented, reflecting varying stages of legislative development across countries.

Despite regulatory disparities, several nations have introduced AI governance frameworks to ensure safe adoption while fostering innovation. However, these regulations are often not specific to the transport sector, with few dedicated models for AI oversight in road infrastructure. Key concerns include data requirements, security, and privacy risks, which are addressed through comprehensive data protection laws in most countries. While AI-specific legislation remains limited, existing data protection laws still apply to AI deployment.

The following sections provide an overview of global AI governance, highlighting progress, gaps, and legislative challenges in the road sector.

9.1.15. Europe

As part of its digital strategy, the EU has introduced the EU AI Act, the world's first comprehensive legal framework for AI. Passed by the EU Parliament on 13th March 2024, it will take effect on 1st August 2024, with most provisions commencing on 2nd August 2026. The Act follows a risk-based approach, classifying AI technologies into Unacceptable-Risk, High-Risk, and Limited-Risk categories. Unacceptable-Risk AI, including cognitive behavioural manipulation, social scoring, and behaviour-distorting categorisation, is prohibited due to its significant threats to individuals.

Table B.3: Examples of risk assessments for common traffic management activities developed by TM2.0 in preparation for requirements of ‘high-risk’ activities under the EU AI Act (TM2.0, 2024)

AI Use Case and Description	Risk Assessment
Data Driven Traffic Analytics & Insights – AI algorithms utilised to process large volumes of historical traffic data to identify congestion and accident-prone areas. The advice received by the considered by traffic authorities and is used as a decision support systems for humans rather than the system automatically making a decision.	Low safety criticality
Real-Time Traffic Management – As seen in the case study section, AI and data fusion technologies can be utilised to analyse road networks for incidents and congestion. Alerts are generated from the AI system for any incidents which leaves the traffic operator with the option to take measures to address the incident accordingly. The decision is made by the human traffic operator.	Low safety criticality
Adaptive Speed Limits – For use cases where AI is used to optimise throughput on road networks, where speed limits are automatically updated based on the data received by the AI system. The functional space is defined by the speed limits that are possible to display on the signs. In a case where there are signs displaying different speeds on adjacent lanes there can be an elevated accident risk by inducing discrepant speed patterns.	Medium safety criticality
Responsive and Adaptive Control – An AI system which helps generate optimal plans for traffic demands based on real-time traffic conditions. For example, traffic lights that are constantly adapting to real-time conditions rely on safety mechanisms to manage most operational scenarios. However, the challenge lies in ensuring that failure states are adequately designed to account for all possible scenarios, including rare and extreme conditions. The functional space contains every possible state of actuated signals, including green/green conflicts and other hazards, making robust failure state design critical.	High safety criticality

The EU AI Act imposes varying compliance requirements based on risk classification. Limited-Risk AI systems, such as chatbots and deepfake detection, require transparency measures but face minimal regulation. Minimal-Risk AI is exempt from compliance, while High-Risk AI - including systems managing critical infrastructure and road traffic - is subject to strict oversight. Annex III of the Act defines High-Risk AI, encompassing safety-critical digital infrastructure. AI systems that trigger automated changes without human intervention and with unlimited possible outcomes fall into this category. The Act outlines distinct obligations for AI providers and deployers. Deployers of High-Risk AI must implement technical and organisational measures, ensure compliance with usage guidelines, and appoint qualified personnel for oversight. Providers must ensure compliance with the Act’s requirements. Non-compliance may result in fines of up to €15 million or 3% of global annual turnover, whichever is higher (EU AI Act, 2024).

TM2.0, an innovation platform for interactive traffic management, has published a position paper on the Act's implications for road traffic management. It stresses the need for a risk assessment framework within the traffic management data decision chain, covering data collection, transformation, and functional space definition. This functional space, shaped by human input, is crucial in assessing AI-related risks.

The paper argues that High-Risk AI should be restricted to decision-support and automated decision-making in contexts where malfunctions pose risks to health, safety, or fundamental rights. Risk evaluation should consider scale, duration, and severity of public safety concerns. It advocates stakeholder engagement to define genuine High-Risk use cases and warns against sector-wide risk labelling, recommending individual case assessments to balance regulation and innovation in traffic management.

Meanwhile, the UK has introduced a National AI Strategy promoting AI growth, research, and investment. Adopting a pro-innovation regulatory approach, the UK government aims to support innovation while managing risks, advocating for a context-specific and proportionate regulatory framework. Rather than imposing new legislation, the UK strategy focuses on leveraging existing laws to address risks and establish AI safeguards.

9.1.16. North America

The US currently lacks comprehensive federal legislation regulating AI. Instead, existing laws apply to AI-related activities, requiring providers and deployers to anticipate regulatory obligations. On 30th October 2023, an executive order on the Safe, Secure, and Trustworthy Development and Use of AI introduced new standards for AI and security. The order's key principles include: (i) ensuring AI is safe and secure, (ii) promoting responsible innovation, competition, and collaboration, (iii) supporting American workers, and (iv) advancing equity and civil rights (The White House, 2024).

Although no federal AI law exists, several state-level initiatives have emerged, leading to varied regulatory approaches. The International Association of Privacy Professionals (IAPP) developed a US State AI Governance Legislation Tracker to monitor AI regulations in the private sector (IAPP, 2024). California, Colorado, and Utah have enacted private sector AI governance laws, influencing the regulation of high-risk AI systems. Additionally, the US AI Training Act mandates the Office of Management and Budget to provide AI training for executive agency personnel, ensuring they understand AI capabilities and risks (AI Training Act, 2024).

In Canada, the forthcoming AI and Data Act aims to protect citizens from High-Impact Systems and ensure responsible AI development. Similar to the EU AI Act, this framework categorises High-Impact AI based on its applications. Within the road sector, AI used for service access determination or prioritisation, such as route selection or planning, falls under this category. Regulations will ensure these systems remain free from inherent bias, preventing discriminatory service provision (IAPPAI, 2024).

9.1.17. Asia

The diversity in social, technological, and economic development across Asia has resulted in varied AI regulations and guidance. In China, the Interim Measures for the Management of Generative AI

Services, effective 15th August 2023, do not implement explicit risk categorisation but suggest that certain AI services, particularly those related to infrastructure and the road sector, face stricter regulatory scrutiny (White Case, 2024). India currently lacks specific AI regulations, but the proposed Digital India Act aims to replace the IT Act of 2000, introducing regulation for high-risk AI systems while supporting technological innovation (IAPP AI, 2024). Similarly, Japan has no dedicated AI legislation but introduced the AI Guidelines for Business on 19th April 2024, promoting 'agile governance', where nonbinding guidance encourages the private sector to self-regulate (White Case, 2024). Singapore also lacks specific AI laws but has developed a draft Model AI Governance Framework for Generative AI (2024), addressing accountability, data security, trusted data sources, and testing (White Case, 2024).

9.1.18. Africa

The adoption of AI technologies in African countries remains less advanced compared to Europe and North America, resulting in limited comprehensive legislation. In Egypt, while no direct AI regulations exist, the government has introduced a National AI Strategy aimed at developing skills, technology, ecosystems, and governance frameworks to support sustainable AI growth (The National Council for AI, 2021). Kenya also lacks specific AI legislation, though a national AI strategy is under development. Existing laws, such as the Data Protection Act (2019), impact AI by granting individuals the right to avoid decisions based solely on automated processing. Additionally, the Robotics and AI Bill (2023) requires AI and robotics businesses to register with the government, outlining their intended activities (White Case, 2024).

9.1.19. Latin America

As in much of the world, AI regulation in Latin America remains limited, though some countries are progressing toward future legislation. Brazil has proposed a comprehensive AI Bill focused on the ethical and responsible use of AI. The Bill aims to prohibit excessive-risk AI systems, establish civil liability for AI providers, and create a regulatory body to enforce compliance (Access Partnership, 2023). Additionally, existing laws such as the General Data Protection Law (2018) impact AI applications involving personal data collection, particularly in computer vision technologies. Peru has introduced Law 31814, promoting AI for economic and social development. Its key principles include risk-based security standards, a multi-stakeholder approach, and AI privacy protections. Mexico has proposed the creation of the Mexican Agency for the Development of Artificial Intelligence, a decentralised public body with technical and managerial autonomy, aiming to formulate a national AI strategy and oversee its responsible use². In El Salvador, while specific AI legislation is still under development, the government emphasizes a human-centered approach to AI applications, ensuring they are based on human rights, are secure, safe, and promote economic growth³.

9.1.20. Oceania

Australia has not yet introduced specific AI regulations, though existing laws such as the Privacy Act (1988) and Corporations Act (2001) may impact AI development. In June 2023, the government released a discussion paper inviting public consultation on AI governance. An interim response,

² [AI-Paper-Case-Study-Mexico_V1.pdf](#)

³ [GDC-submission_El-Salvador.pdf](#)

informed by stakeholder feedback, highlighted gaps in existing laws, particularly regarding high-risk AI systems. Consequently, the government is considering mandatory safety guardrails for AI development and use (Australian Government, 2024). Similarly, New Zealand lacks comprehensive AI regulation, though the Privacy Act (2020) governs AI-related data usage. Many agencies adhere to the Algorithm Charter, which includes a risk matrix for evaluating algorithmic applications and establishing ethical AI commitments (IAPP AI, 2024). Despite legislative progress, the impact on NRAs remains uncertain. Future AI regulations will impose data protection, safety compliance, and risk assessment requirements. ISO, IEEE, and SAE play key roles in AI governance for road transport, developing standards to ensure interoperability and safety. As noted on page 94, ISO's AI and transportation standards support compliance and innovation, making global regulatory alignment essential for NRAs.

APPENDIX C: STAKEHOLDER ENGAGEMENT: DETAILED FINDINGS

This section presents the detailed survey and interview results from stakeholder engagement.

SURVEYS

The surveys provide insights into AI applications, challenges, and future implementation in the road sector. The findings offer an overview of technological maturity, AI adoption, and expected benefits and barriers to integration by 2030. As previously mentioned, the survey comprised 29 questions, beginning with inquiries about respondents' organisations, roles, and key challenges. Participants then provided insights into the technological infrastructure in their regions and the extent of AI integration in their road sector operations.

Q1 required respondents to accept the terms and conditions of participation to allow them to proceed to answer the survey. In Q2, the respondents were asked to provide the name of their organisation while in Q3 they were asked to classify the nature of their organisation. The results from Q3 are shown in Figure C.1.

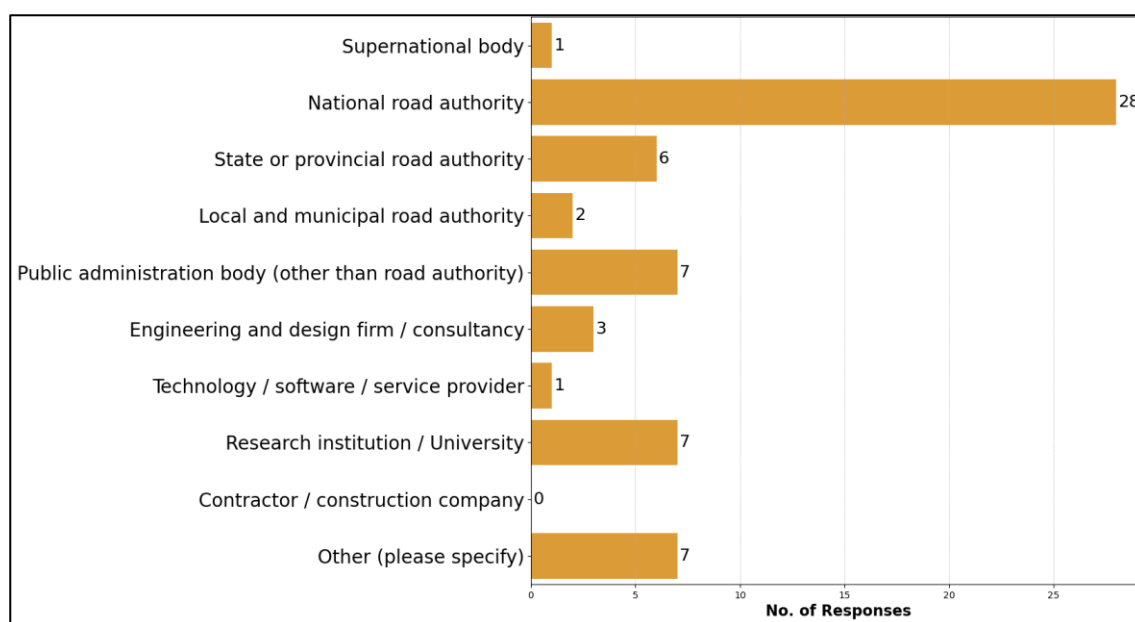


Figure C.1: Q3. Which best described the organisation you represent?

The survey results for Q3 show that the majority of respondents (28 out of 62, or 45%) represent NRA. State or provincial road authorities contributed 6 responses (10%), while local and municipal authorities had minimal representation with only 2 response (3%). Research institutions and public administration bodies, other than road authorities, accounted for 7 (11%) and 7 (11%) responses respectively. There were also contributions from engineering and design firms (5%), technology providers (2%), and a significant “Other” category (11%) which consisted of other road management related organisations, reflecting a diverse range of stakeholders. Table C.1 presents the responses received for Q4, while Figure C.2 illustrates their geographical distribution and socio-economical variation. In Figure C.2, it can also be seen that most of the responses came from HICs (50 out of 62, or 81%), while the UMICs and Lower MICs+LICs accounted for 8 out of 62, or 13% and 4 out of 62, or 6%, respectively. However, there was a good spread of responses amongst all

continents which has allowed for a diverse range of results to the survey. Owing to the limited number of responses received from Lower MICs and LICs (two responses each), their data were combined and presented collectively as Lower MICs+LICs.

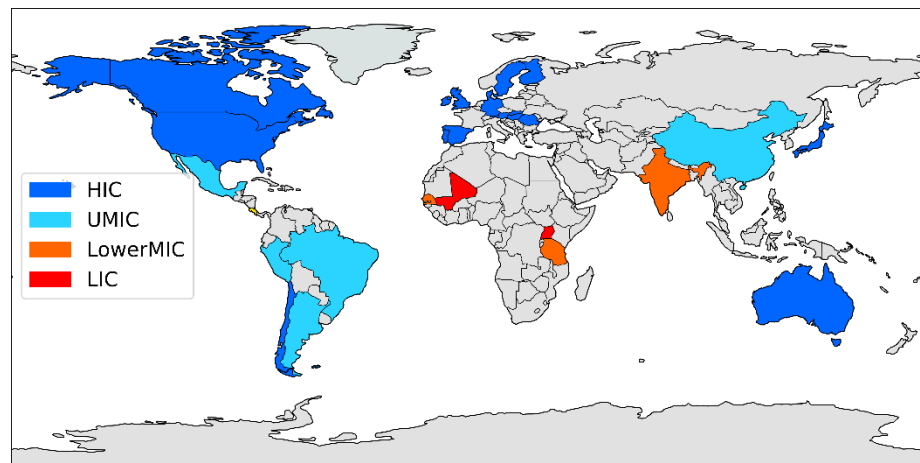


Figure C.2: Overview of survey respondent's geographical distribution and socio-economical variation.

Table C.1: Q4. Which country is your organisation based in?

Country	No. of Responses	Income Class
Argentina	2	UMIC
Australia	6	HIC
Austria	3	HIC
Canada	10	HIC
Chile	1	HIC
China	1	UMIC
Costa Rica	4	UMIC
Czech Republic	2	HIC
Denmark	1	HIC
Finland	2	HIC
Germany	1	HIC
Hungary	1	HIC
Ireland	5	HIC
Japan	5	HIC
Mali	1	LIC
Mexico	1	UMIC
Portugal	1	HIC
Romania	2	HIC
Senegal	1	LowerMIC
Singapore	2	HIC
Slovakia	1	HIC
Spain	1	HIC
Sweden	1	HIC
Uganda	1	LIC
United Kingdom	1	HIC
United Republic of Tanzania	1	LowerMIC
United States of America	4	HIC

The survey results for Q5 revealed a varied distribution of professional roles among the respondents. The largest group, representing 28%, comprised directors and heads of departments, indicating a strong presence of senior management. Managers, responsible for projects, programmes, or services, accounted for 20% of the respondents while engineers made up 19%. Founders, CEOs, or chiefs contributed 11%, while professors and researchers represent 9%, highlighting academic engagement. The remaining 13% fell into the “Other” category, suggesting a diversity of roles beyond the predefined categories. Figure C.3 provides a general overview of the roles of respondents.

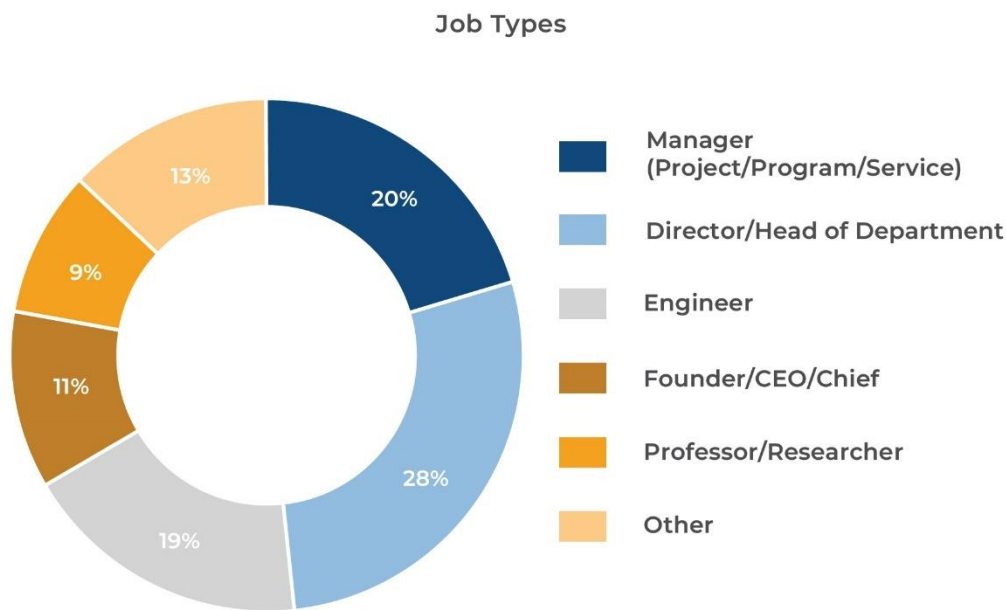


Figure C.3: Q5. Please indicate your professional role / job title.

The responses to Q6 indicated a wide range of experience levels among the participants. The largest group, with 22 respondents (35%), reported having 11 to 20 years of experience in their roles or other relevant positions related to roads.

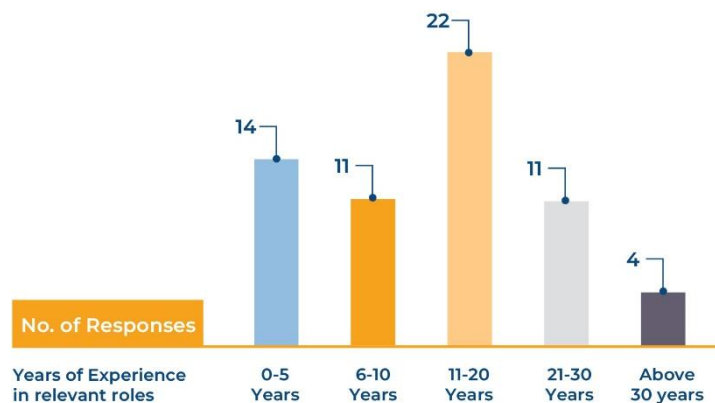


Figure C.4: Q6. How many years have you been in this role, or other relevant positions related to roads?

Fourteen respondents (23%) had between 0 to 5 years of experience, while 11 participants (18%) had worked for 6 to 10 years. Another 11 respondents (18%) reported having 21 to 30 years of experience, reflecting significant expertise in the sector. Finally, 4 respondents (6%) indicated having more than 30 years of experience. Figure C.4 presents a summary of the responses.

The responses to Q7 highlighted a wide range of expertise across various road infrastructure assets. The most frequently cited area of expertise was ITS equipment, with 29 respondents (47%) indicating involvement in assets such as traffic signals, CCTV, and sensors. Pavements were noted by 23 respondents (37%), and structures (bridges, tunnels, gantries, retaining walls, etc.) were

identified by 22 respondents (35%). Road drainage, cycle/pedestrian infrastructure, and road furniture/other (e.g., traffic signs and road markings) were each mentioned by 12 to 14 respondents (19-23%). Earthworks were the least common area of expertise, with 7 respondents (11%). Similarly, seven participants selected “Other”, encompassing diverse specialisations such as hydraulics, ITS regulation, and vehicle cybersecurity. One respondent indicated “N/A.”. Figure C.5 presents the responses received.

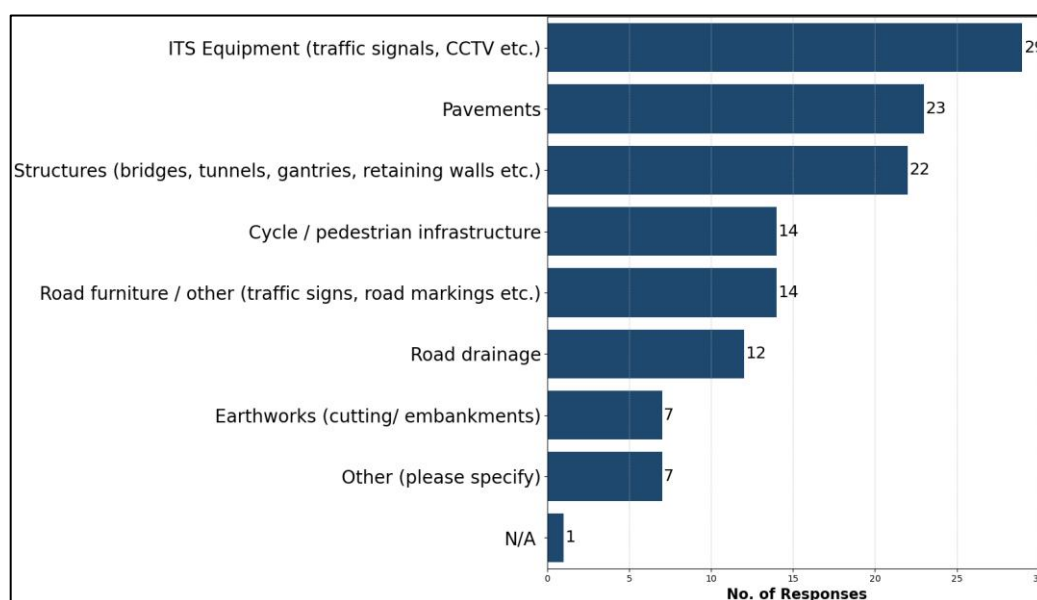


Figure C.5: Q7. Which road infrastructure asset do you work with or possess expertise in? Please select all that apply.

The responses to Q8 illustrated a diverse range of activities in which participants were involved or had prior expertise. The results are shown in Figure C.6. The most frequently cited area was road operations, traffic management, and incident management, with 28 respondents (46%) indicating their involvement in these activities. Following closely, 27 participants (44%) reported expertise in infrastructure inspection or monitoring. Asset management and planning/feasibility studies each garnered 25 responses (41%), while project management was cited by 24 respondents (39%). Infrastructure maintenance, repairs, or rehabilitation, and policy development were each noted by 21 respondents (34%), and road safety received 20 responses (33%). Design of road infrastructure attracted 18 participants (30%), while finance and funding/procurement were mentioned by 15 respondents (25%).

Other notable areas included tolling (11 respondents, 18%), construction (10 respondents, 16%), environmental impact assessment (9 respondents, 15%), and decarbonisation (9 respondents, 15%). Resilience planning was indicated by 7 respondents (11%), and winter services/management received the fewest responses, with 3 participants (5%) involved in this area. The variety of responses underscores the multifaceted nature of expertise within the road sector, emphasising the breadth of stakeholder engagement in these critical areas.

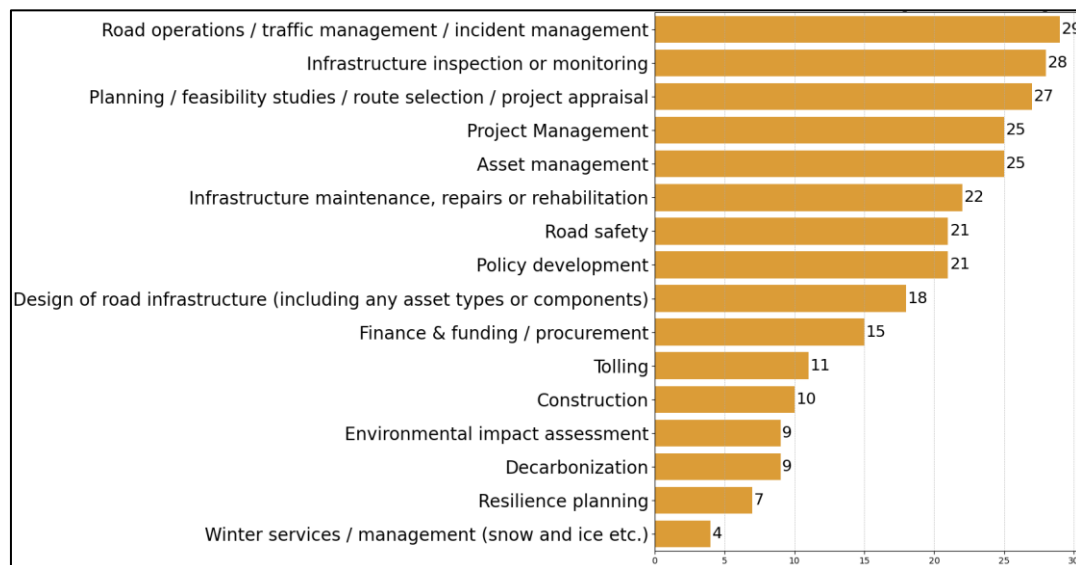


Figure C.6: Q8. Which of the following activities are you typically involved in, or do you have previous expertise in? Please select any that apply. If your choice is not included, please use the “Other” option to provide details.

The survey results concerning the key challenges faced in the road sector underscored a variety of concerns, which respondents rated as low, medium, or high risk. Figure C.7 presents the findings. Infrastructure deterioration emerged as the most significant challenge, with 29 respondents (48%) rating it as high risk, while only 3 (5%) viewed it as low risk. This finding indicates a strong consensus on the urgent need for attention to aging infrastructure. Traffic congestion was another major concern, with 19 participants (31%) identifying it as a high risk. However, 7 respondents (11%) classified it as low risk, suggesting that some stakeholders perceive congestion as more manageable. In terms of safety, construction safety issues elicited varied responses, with 26 participants (43%) considering it a medium risk, while only 6 (10%) indicated high risk, reflecting differing levels of concern about safety practices on construction sites.

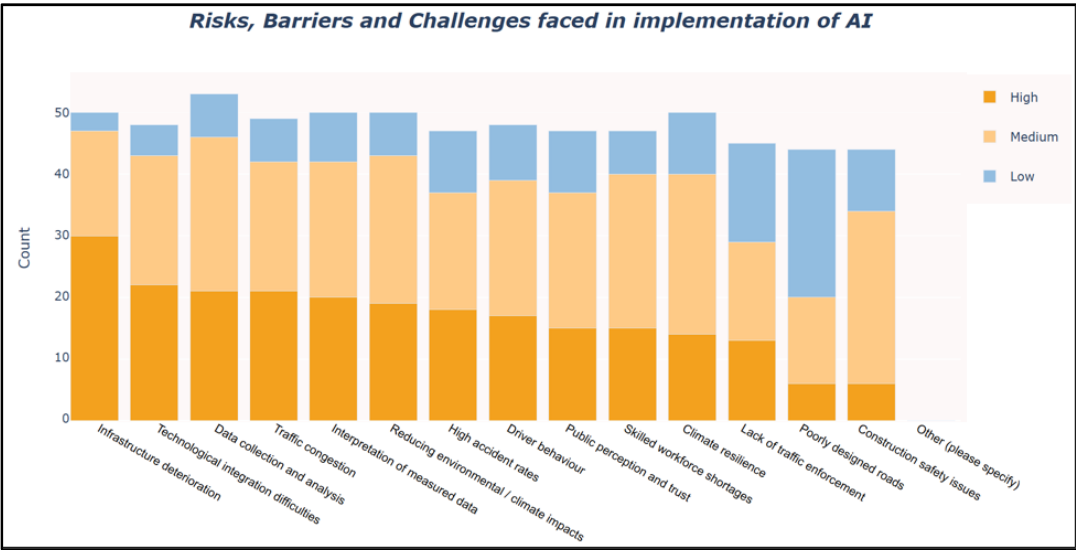


Figure C.7: Q9. In your opinion what are the key challenges in the roads sector or for you in your role? From the list below, please indicate how much of a challenge each item represents. You may ignore/skip any items which are not relevant to you. If there are any key challenges not listed, or you would like to elaborate on those in the list, please use the “Other” option to provide a description.

High accident rates were viewed as a significant challenge by 18 respondents (30%), while concerns regarding poorly designed roads were less pronounced, with 23 respondents (38%) rating it as low risk. Technological integration difficulties were regarded as high risk by 21 participants (34%), emphasising the complexities of adopting new technologies in the sector. Additionally, skilled workforce shortages posed moderate challenges for 25 respondents (41%), highlighting the need for training and capacity-building initiatives.

The survey results concerning the current level of technological infrastructure in the road sector revealed significant variations across countries. Figure C.8 presents the results received from Q10. The definition of Very Low to Very High rating is shown below.

Very Low	Basic road infrastructure with minimal technological integration, limited or no traffic signals except on major routes or junctions, underdeveloped systems for road maintenance, safety, and communication.
Low	Basic traffic signals and signage on major routes, initial use of technology for road maintenance (e.g., basic monitoring systems), basic safety systems (e.g., limited road safety data collection), minimal communication infrastructure supporting road technology.
Moderate	Standard traffic signals and signage on most routes, moderate use of technology for road maintenance and monitoring, developing safety systems with some data collection and analysis, developing communication networks supporting road technology.
High	Advanced traffic management systems with widespread use of technology, well-developed road maintenance systems using modern technology (e.g., predictive maintenance), comprehensive safety systems with real-time data collection and analysis, strong communication networks supporting integrated road technologies.
Very High	Comprehensive smart road networks with extensive use of advanced technology, highly advanced road construction and maintenance systems using cutting-edge technology (e.g., automated construction equipment), integrated and real-time safety systems with predictive analytics, highly developed communication infrastructure enabling seamless integration of various road technologies.

A total of 58 responses were recorded. Among the respondents from HICs (46), 20 (44%) rated their infrastructure as moderate, while 19 (41%) considered it high, reflecting robust technological integration in these regions. Only 1 respondent (2%) indicated a very high level of technological infrastructure. In contrast, 2 HIC respondents (4%) rated their systems as low, and 1 (2%) as very low, indicating that while many HICs have advanced systems, there are still areas in need of improvement. Notably, 2 respondents (4%) expressed uncertainty regarding their country's infrastructure level, illustrating some lack of clarity or information.

Respondents from Lower MICs+LICs presented a different picture. Three respondents (60%) rated their infrastructure as very low, and 1 respondent (20%) each rated it as low and high. Additionally, there were 5 respondents (71%) from UMICs that rated their technological infrastructure as low.

The responses demonstrate a clear distinction between the infrastructural capabilities of high-income nations and those of lower-income regions, emphasising disparities in technological advancement within the road sector. In particular, there may be less variation across Lower MICs+LICs, as the level of technological infrastructure tends to be uniformly low throughout these countries. This uniformity contrasts with the greater variation observed in HICs and Lower MICs+LICs, where regions or sectors with higher levels of technological integration coexist with those requiring significant improvement.

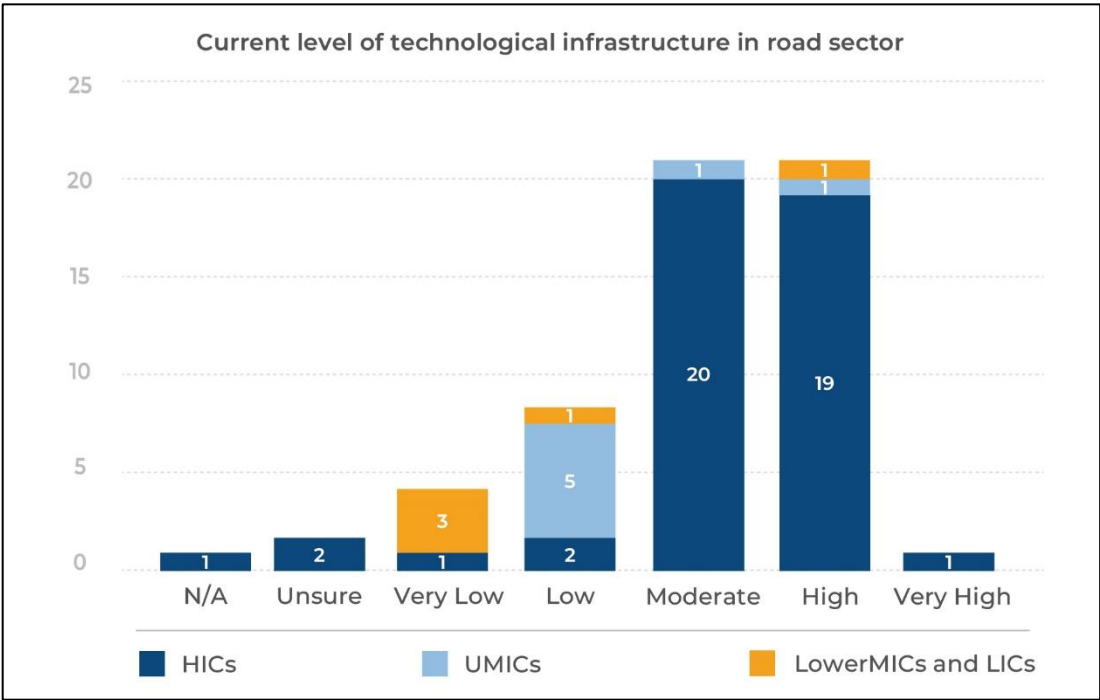


Figure C.8: Q10. What is the current level of technological infrastructure in the roads sector in your country? Please select the option which best represents your country.

The survey results regarding the variation in technological infrastructure within the road sector across different regions revealed significant disparities. The results of Q11 are shown in Figure C.9. The definitions of ‘Very Low’ to ‘Very High’ are shown below.

Very Low	Minimal differences in technological development between regions. Most regions have similar levels of infrastructure and technology.
Low	Some differences in technological development between regions. Urban areas may have slightly more advanced systems compared to rural areas.
Moderate	Noticeable differences in technological development between regions. Urban areas generally have more developed infrastructure and technology compared to rural areas.
High	Significant differences in technological development between regions. Urban areas have advanced systems and infrastructure, while rural areas have less development.
Very High	Extensive differences in technological development between regions. Urban areas have highly advanced and integrated systems, while rural areas have minimal technological infrastructure.

Out of 58 responses, a notable 20 respondents (34%) classified the variation as moderate, indicating that urban areas generally had more developed infrastructure compared to rural settings. Furthermore, 15 respondents (26%) rated the variation as high, underscoring the substantial gap between urban and rural technological capabilities.

Conversely, 5 respondents (9%) expressed uncertainty about the level of variation, while 4 (7%) deemed the differences very low, suggesting minimal discrepancies in technological development

across regions. This was particularly evident in responses from Lower MICs+LICs, which accounted for the majority of these ‘Very Low’ responses, potentially reflecting the relatively low level of technology throughout these countries. A total of 9 participants (16%) rated the variation as low, noting some advancements in urban areas but not significantly different from rural counterparts. In contrast, 5 respondents (9%) identified very high variation, highlighting extensive differences, particularly where urban areas exhibited highly integrated systems while rural areas lacked basic infrastructure.

These findings emphasise the challenges faced in achieving equitable technological advancement across regions, which may hinder the overall effectiveness of AI integration in the road sector.

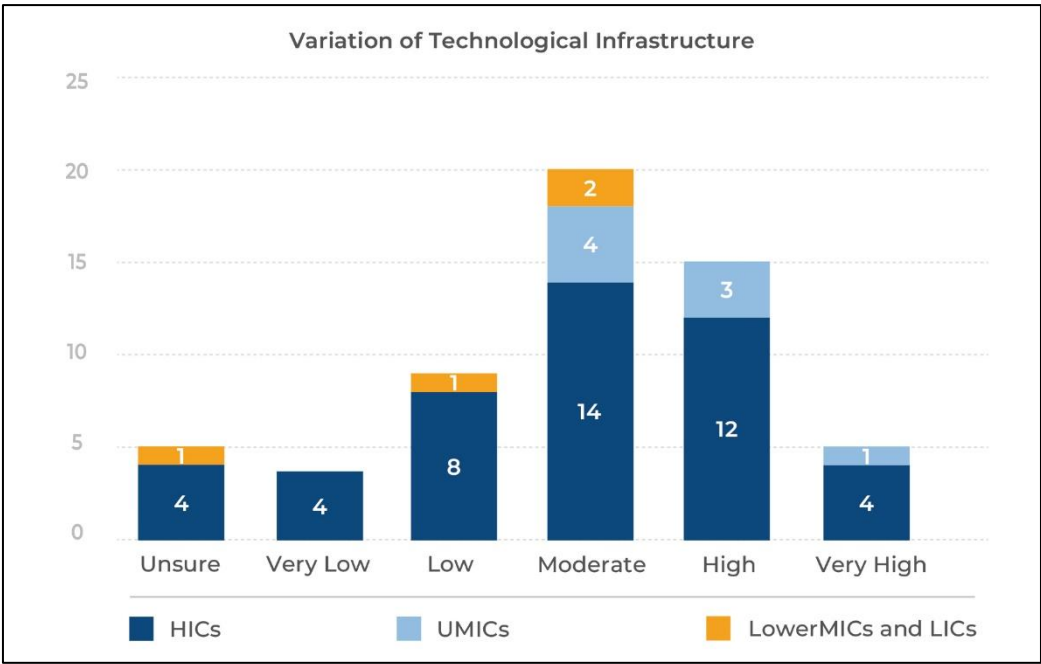


Figure C.9: Q11. How would you describe the level of variation in technological infrastructure in the roads sector between different regions in your country (e.g., urban vs. rural areas)?

Q12 was posed to get an understanding of the level and quantity, quality and accessibility of datasets available in the country of the respondent. Large amounts of accurate data are required for most AI systems in order to operate at an efficient and effective matter.

The Q12 survey results concerning the quantity of datasets available in the road sector highlight a variety of gaps and strengths across different data categories, as rated by respondents. Figure C.10 presents the findings. Pavement/structure condition data emerged as one of the most readily available datasets, with a notable number of respondents rating it as high availability. This indicates that this dataset is generally prioritised across many countries. However, some respondents still rated its availability as medium or low, highlighting potential inconsistencies in data accessibility.

Traffic data, including network usage, speeds, and journey times, was another critical area of focus. A significant number of respondents rated its availability as medium or high, reflecting its essential role in operational management and planning. Conversely, low availability ratings were also common, indicating disparities in the extent to which traffic data is collected or shared across regions. Spatial/GIS data and information on traffic accidents also showed notable responses. While these datasets were generally rated as medium or high by many respondents, a considerable

number indicated low or non-existent availability. This suggests that while some countries have developed robust systems for collecting and utilising these datasets, others lag behind.

Air and noise pollution data exhibited one of the lowest levels of availability, with a large proportion of respondents rating it as low or non-existent. This points to a significant gap in environmental data collection, which is critical for assessing the impact of road networks on surrounding communities. Condition data for ITS assets and detailed “as-built” data similarly showed low availability ratings for many respondents. These results indicate significant challenges in maintaining accurate and updated records of ITS and infrastructure specifications, which are essential for effective planning and maintenance. Finally, customer satisfaction data had the lowest availability ratings, with a majority of respondents marking it as low or non-existent. This highlights a critical gap in understanding user perspectives, which can inform improvements in road network quality and functionality.

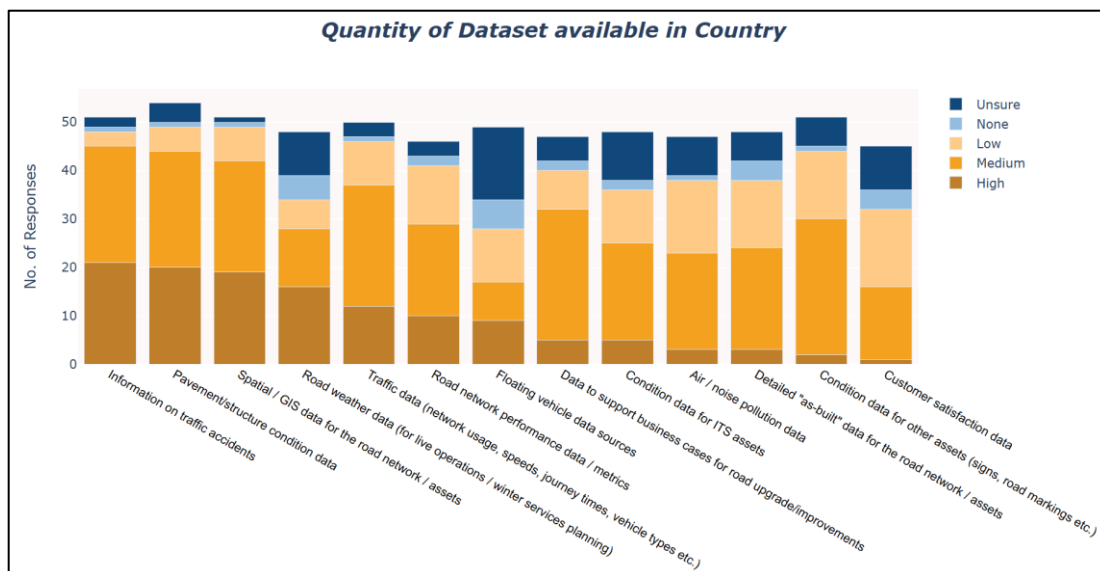


Figure C.10: Q12. For each of the different types of data listed below, please indicate the "Quantity" in your country/jurisdiction. These data sources are typically used to assist decision-making in the activities mentioned. You may ignore/skip any items which are not relevant to you. For any relevant data sources not listed, or to elaborate on those in the list, please use the "Other" option to provide a description.

The results highlighted in Figure C.10 revealed that 'Information on traffic accidents', 'Pavement/structure condition data', 'Spatial/GIS data for the road network/assets' are the datasets with the highest quantities available according to respondents. Figure C.11 and Figure C.12 present the quality and accessibility of the listed datasets and their corresponding levels respectively. There are similar results to the previous question shown on the quantity of available datasets. The results also clearly indicate that 'condition data for other assets' and 'customer satisfaction data' are lacking in the countries of the respondents to the survey.

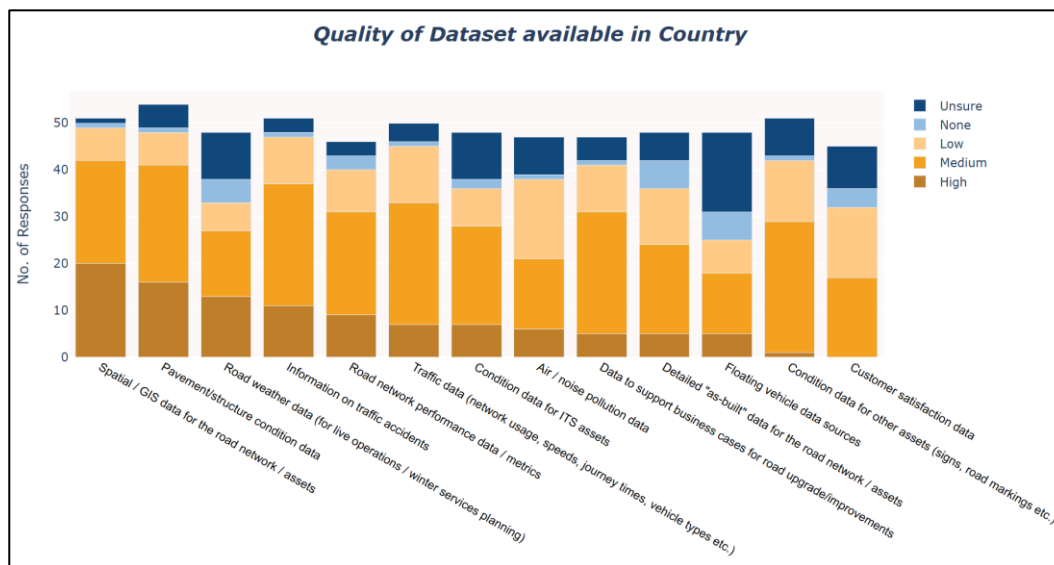


Figure C.11: Q12. For each of the different types of data listed below, please indicate the "Quality", and in your country/jurisdiction. These data sources are typically used to assist decision-making in the activities mentioned. You may ignore/skip any items which are not relevant to you. For any relevant data sources not listed, or to elaborate on those in the list, please use the "Other" option to provide a description.

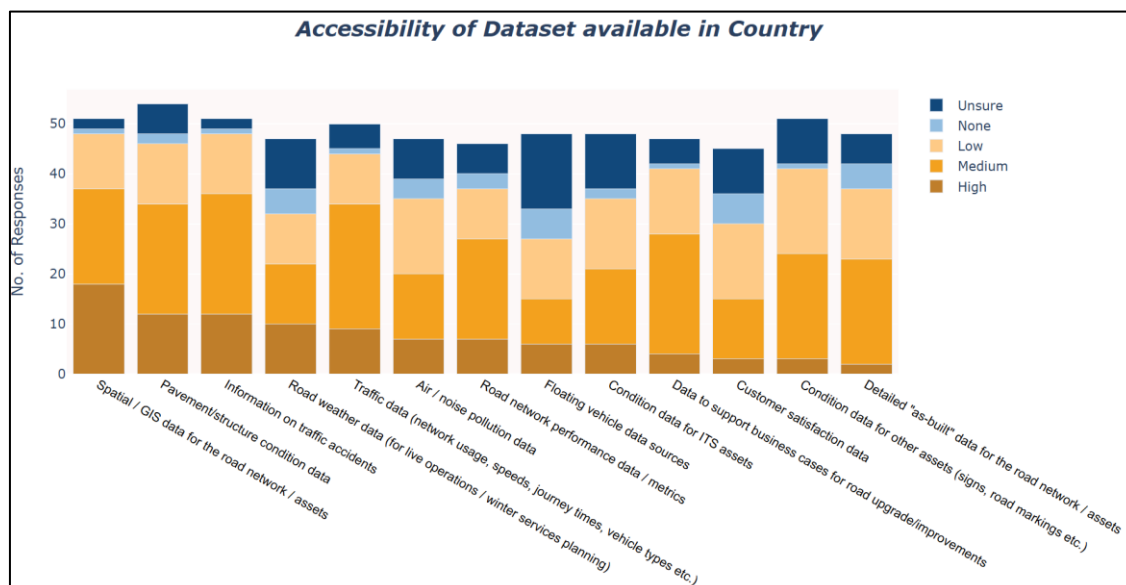


Figure C.12: Q12. For each of the different types of data listed below, please indicate the "Accessibility" in your country/jurisdiction. These data sources are typically used to assist decision-making in the activities mentioned. You may ignore/skip any items which are not relevant to you. For any relevant data sources not listed, or to elaborate on those in the list, please use the "Other" option to provide a description.

Q13 focused on determining whether AI was being used for any road sector activities, asking respondents to indicate whether their organisations were currently employing AI. Figure C.13 outlines the results, separating responses from HICs, UMICs and Lower MICs+LICs.

Out of 57 total responses, 33 (58%) indicated that their organisations were currently using AI in some capacity, with the majority - 27 respondents - from HICs. Both Lower MICs+LICs and UMICs had 3 respondents each reporting AI usage, demonstrating a significantly lower level of adoption

compared to HICs. In contrast, 17 (30%) respondents reported that their organisations were not employing AI technologies. This group included 7 respondents from HICs, alongside 5 respondents each from Lower MICs+LICs and UMICs, indicating that barriers to AI adoption persist even in higher-income regions. Additionally, 7 (12%) respondents were unsure about the use of AI within their organisations. This group predominantly consisted of 5 respondents from HICs, with 1 respondent from Lower MICs+LICs and 1 from UMICs, suggesting potential gaps in internal communication or awareness about AI usage.

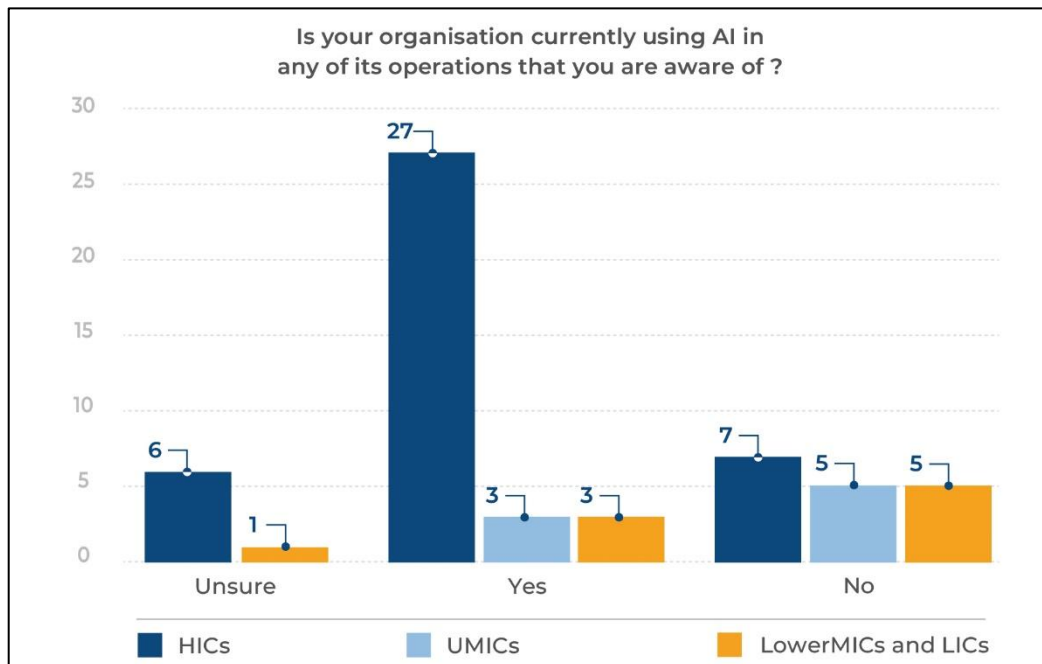


Figure C.13: Q13. Is your organisation currently using AI in any of its operations that you are aware of?

Q14 aimed to gain an understanding of the road sector activities within organisations currently utilising AI. This question was shown only to respondents who had answered “Yes” in the previous question. The results are illustrated in Figure C.14, with a total of 46 responses recorded.

The most prominent application of AI was in road operations, traffic management, and incident management, reported by 14 respondents (30%). This highlights the growing reliance on AI for real-time decision-making and operational efficiency in this domain. Infrastructure inspection or monitoring was the second most cited application, mentioned by 9 respondents (20%), followed closely by asset management, which was also noted by 9 respondents (20%). AI use in road safety was reported by 7 respondents (15%), indicating its role in enhancing safety measures and reducing risks. Planning, feasibility studies, route selection, and project appraisal saw participation from 6 respondents (13%), while project management and tolling were each noted by 3 respondents (7%).

Additionally, 4 respondents (9%) cited other uses of AI within their organisations, such as internal administrative processes. This indicates that AI may offer significant internal benefits that extend beyond road-specific activities. It is noteworthy that AI applications in areas such as finance, funding, and procurement received no responses, highlighting a potential gap in its application for financial management within the road sector. Less common uses of AI included areas such as resilience planning, environmental impact assessment, and decarbonisation, each with only 2 or 1

respondent(s), reflecting nascent adoption in these fields. Similarly, AI in construction, winter services/management, and policy development were noted by just 1 respondent each.

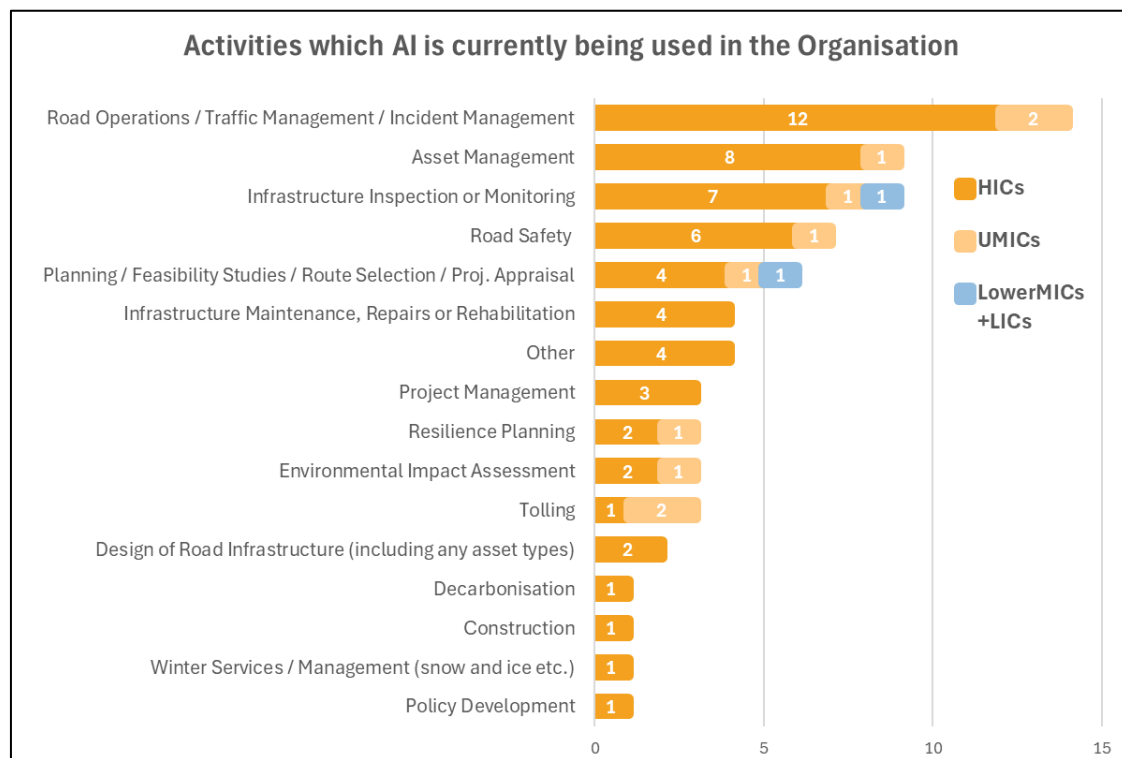


Figure C.14: Q14. In which activities is AI currently being used within your organisation? Please select any that apply. If AI is being used in another area, not listed below, please use the "Other" option to provide details.

Q15 was an open-response question directed at respondents currently utilising AI within their organisations. This question offered the opportunity to provide specific details regarding AI applications in use. The results are summarised in Figure C.15, which highlights the key areas of AI utilisation. The most prominent activity identified was road operations, traffic management, and incident detection, accounting for 48% of responses. This reflects the widespread AI adoption in improving operational efficiency and real-time traffic management, with incident detection being specifically mentioned across five different countries.

Another notable application was infrastructure inspection or monitoring, highlighted by 16% of respondents. Many participants detailed the use of computer vision for tasks such as pavement condition assessments, underscoring AI's role in enhancing infrastructure maintenance processes. AI usage in road safety was noted by 13% of respondents, demonstrating its growing importance in reducing accidents and improving safety outcomes through advanced analytics and predictive modelling.

Finally, 23% of respondents mentioned other applications of AI, which included diverse activities ranging from predictive maintenance to administrative functions. This illustrates the flexibility of AI technologies in addressing a wide range of organisational needs beyond traditional road sector operations.

Details of AI Technologies Currently Used Within Organisation

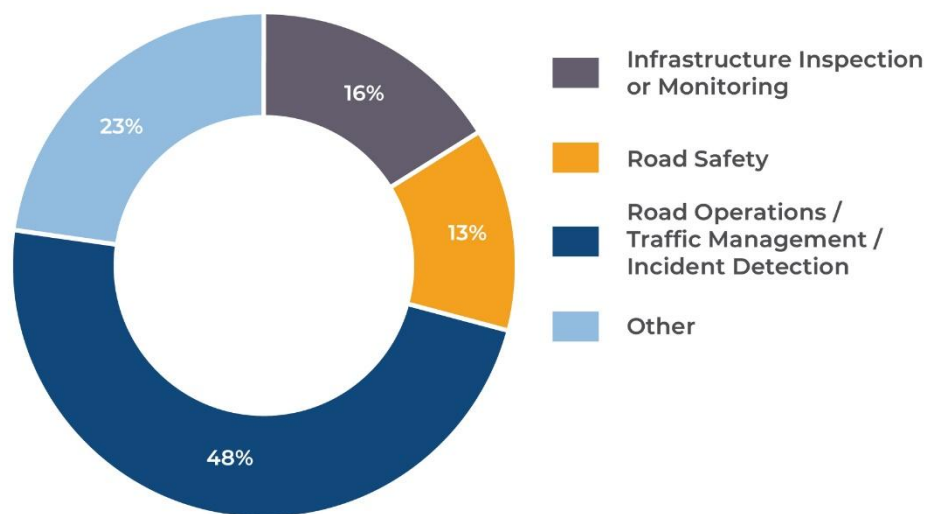


Figure C.15: Q15. You have indicated that AI technology is being used within your organisation. Please use the text box below to provide additional details about the specific uses of AI technology. Please provide details on any particular assets / activities for which it is being used. Please limit your answer to 100 words.

The survey results provided valuable insights into the benefits organisations have achieved through AI implementation in the road sector. Figure C.16 illustrates these findings, highlighting a range of advantages across various operational and strategic areas.

One of the most notable benefits was time savings, which emerged as a key area where AI has proven its value. A significant number of respondents rated the benefits as high, reflecting the ability of AI to streamline processes and accelerate decision-making. This efficiency is particularly critical in managing complex road networks and responding to real-time challenges. Enhanced infrastructure inspection efficiency and accuracy also stood out as a prominent benefit. Many respondents noted medium to high levels of achievement in this area, likely driven by the adoption of technologies such as computer vision and predictive analytics. These tools are enabling organisations to assess infrastructure conditions more effectively, reducing manual effort and improving precision.

The role of AI in improving road safety was another area of recognition. Respondents largely rated the benefits as medium, with AI contributing to better accident prevention and safety management through data-driven insights and monitoring systems. This demonstrates AI's potential to save lives and enhance overall road safety. In asset management, AI was recognised for delivering moderate benefits. While some respondents rated the advantages as high, many noted only medium or low levels of achievement, suggesting that AI's potential in this domain is not yet fully harnessed. Nevertheless, its application in optimising resource allocation and maintenance planning holds significant promise.

Cost savings were identified as another area where AI is making an impact. While many respondents rated the benefits as medium, fewer noted high levels of achievement. This may indicate that cost reductions are not yet fully realised in some organisations, potentially due to the initial investments required for AI adoption. When it came to improvements in network performance, AI was credited

with moderate benefits. Respondents highlighted its role in traffic flow optimisation and congestion management, which are critical for efficient road operations.

Improvements in maintenance practices received similar feedback, with medium ratings dominating. AI's predictive capabilities are evidently aiding in proactive maintenance, but there remains room for greater impact in this area. Interestingly, environmental benefits and decarbonisation were among the areas with the lowest ratings. Many respondents expressed uncertainty or rated the benefits as low, indicating that the potential for AI to support sustainability goals is still underexplored or underdeveloped. AI's role in improving efficiency in administrative processes also received mixed feedback. While some organisations reported moderate benefits, the results suggest that the application of AI in this domain is still in its early stages.

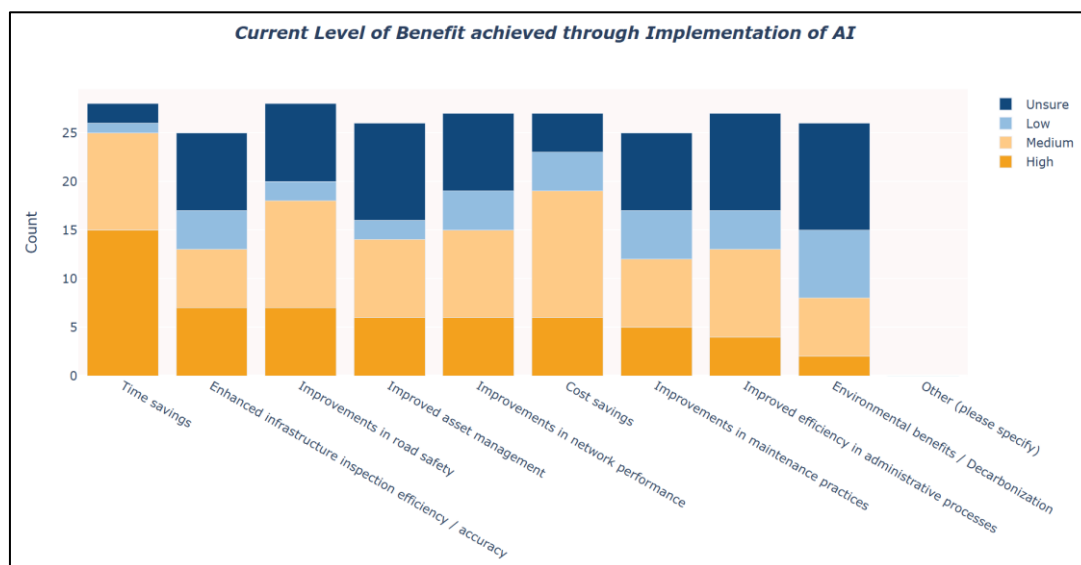


Figure C.16: Q16. You have indicated that AI technology is being used within your organisation. Based on your knowledge, what level of benefit has your organisation observed in the areas listed below? If you have achieved benefits other than those listed below, please use the "Other" option to provide details. You may ignore/skip any items which are not relevant to you.

Q17 was aimed at understanding organisations' future plans up to 2030 regarding the implementation of AI-based technologies. As AI technology is expected to develop significantly in the coming years, the results shown in Figure C.17 indicate that more organisations plan to adopt these technologies.

A total of 40 respondents indicated that their organisations are planning to use or further integrate AI by 2030, which represents a 21% increase compared to the results of Q13, where 33 respondents confirmed current AI usage. This growth underscores the expanding interest in AI adoption across the road sector. When examining responses by income group, 32 respondents from HICs confirmed plans to use AI in their organisations. Additionally, 4 respondents each from Lower MICs+LICs and UMICs also expressed plans for AI implementation.

Interestingly, no respondents from any country or income group stated that they have no plans to introduce AI into their organisations' operations. This suggests that the potential of AI is universally recognised across all regions. However, 11 respondents from HICs and 4 from UMICs indicated that they are unsure about their organisation's future AI plans. This may reflect a lack of clarity in strategic planning or awareness of AI advancements within these organisations. In contrast, no

respondents from Lower MICs+LICs reported uncertainty, possibly indicating more defined organisational perspectives or priorities.

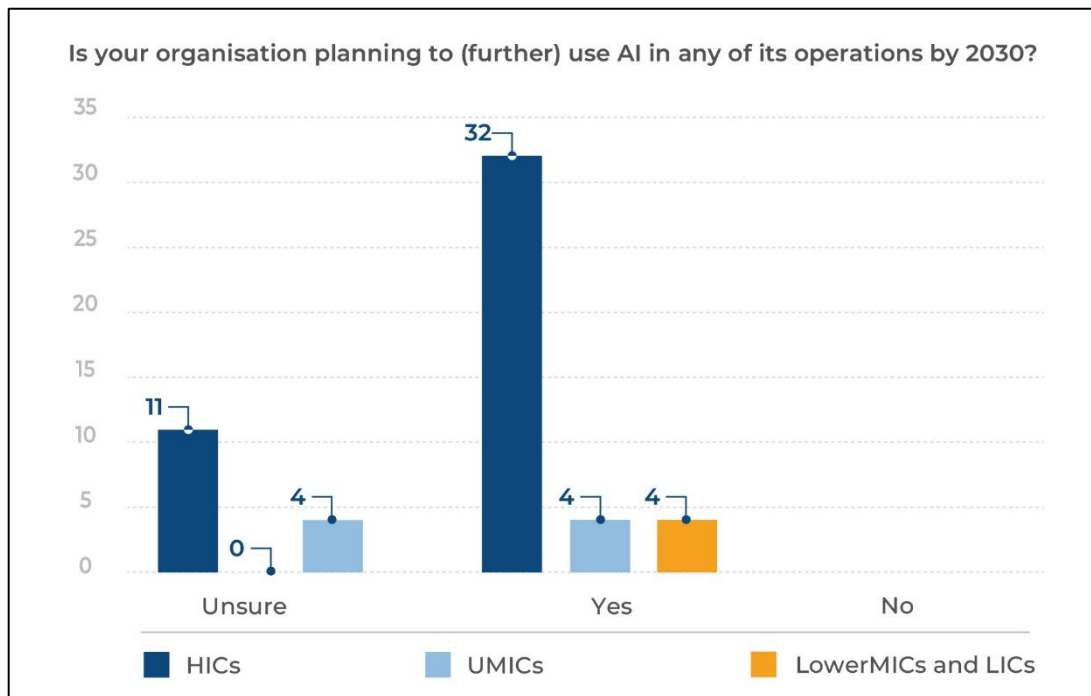


Figure C.17: Q17. Is your organisation planning to (further) use AI in any of its operations by 2030?

Q18 (see Figure C.18) aimed to explore the anticipated future landscape of AI adoption in the road sector, focusing on specific activities organisations are considering for AI implementation by 2030. When compared to Q14, which addressed current AI use, the results of Q18 indicate a notable increase in engagement, highlighting a strong intent to adopt AI technologies in the near future.

The most frequently identified activity for future AI use is asset management, with 20 respondents from HICs and smaller contributions from UMICs and Lower MICs+LICs. This reflects AI's growing role in optimising asset lifecycle management and maintenance planning. Road operations, traffic management, and incident management and infrastructure inspection or monitoring were each cited by 18 respondents from HICs, indicating the continued prioritisation of AI for operational efficiency and real-time decision-making. Similarly, activities such as planning, feasibility studies, route selection, and project appraisal and road safety also emerged as key areas for future AI adoption, with total 19 and 18 respondents respectively recognising their potential.

AI use in infrastructure maintenance, repairs, or rehabilitation was also highlighted, with 13 respondents expressing plans to integrate AI into these activities. Other areas, such as resilience planning and winter services/management, received moderate interest, with 11 and 10 respondents respectively indicating future AI applications in these domains. Notably, some areas such as environmental impact assessment, tolling, and design of road infrastructure attracted less attention, with 9, 8, and 8 respondents respectively. This may indicate that these applications are either less prioritised or currently in the early stages of consideration.

AI for construction-related activities was identified by only 5 respondents, likely due to the limited participation of survey respondents from contractors or construction companies. However, as noted in the literature review, there are already numerous examples of AI applications being

successfully employed in construction projects, suggesting that the reported uptake in this area may not fully reflect its future potential. Less common applications, including policy development, finance and funding/procurement, and decarbonisation, were identified by only 4 and 3 respondents each. The 3 “Other” responses included the use of AI for managing or maintaining guidelines and for administrative tasks. These responses point to gaps in AI adoption for strategic and sustainability-focused activities, which may require additional advocacy or development to reach their potential.

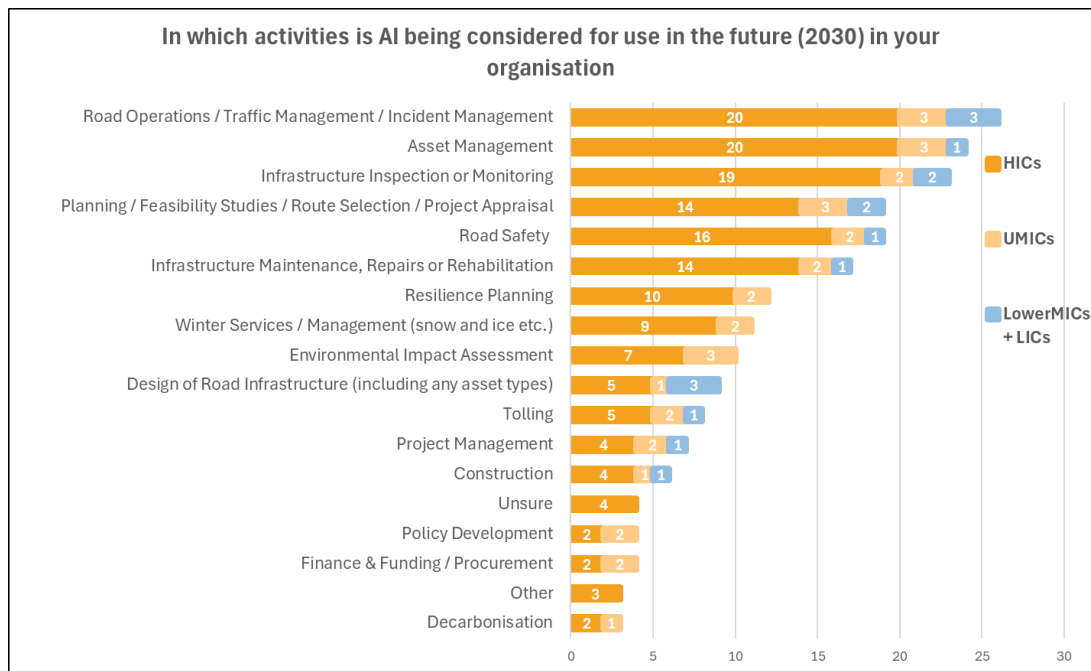


Figure C.18: Q18. In which activities is AI being considered for use in the future within your organisation up to 2030? Please select all that apply.

Q19 builds upon previous questions, delving deeper into the future use of AI in the road sector. As an open-ended question, similar to Q15, it provided respondents with the opportunity to share their perspectives on the expected development and application of AI technologies up to 2030. The results, summarised in Figure C.19, highlight key areas where stakeholders anticipate deploying AI. The most prominent area identified was road operations, traffic management, and incident detection, accounting for 26% of responses. This underscores the ongoing importance of AI in enhancing traffic flow, improving safety, and responding effectively to incidents. Asset management also emerged as a critical focus area, with 17% of respondents expecting to leverage AI for activities such as asset lifecycle optimisation and maintenance planning. This reflects the growing recognition of AI's potential to improve the efficiency and longevity of road infrastructure.

Infrastructure inspection or monitoring accounted for 22% of responses, highlighting its essential role in ensuring road safety and operational efficiency. The use of AI for tasks such as pavement condition assessments and defect detection demonstrates the potential for these technologies to replace or augment manual inspection processes. Road safety was another key area, making up 9% of responses. This relatively lower percentage may suggest that road safety applications are seen as an established use case rather than a future focus. Nevertheless, AI's ability to predict and mitigate risks remains crucial in this domain. The “Other” category, which accounted for 26% of responses, encompassed a diverse range of anticipated applications. These included AI for planning

and feasibility studies, general AI investment, and its use in reporting and task management. This diversity reflects the flexibility of AI technologies to address varied organisational needs beyond traditional road sector applications.

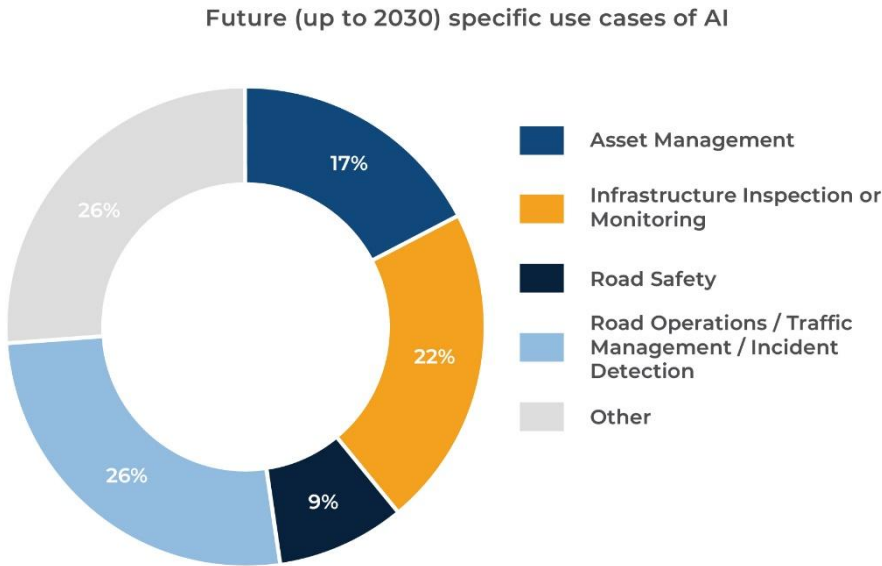


Figure C.19: Q19. You have indicated that your organisation plans to introduce/use AI technology by 2030. If you are aware of the details of the planned usage of AI, please use the text box below to provide further details. Please limit your answer to 100 words.

The survey results for Q20 highlight significant optimism about the expected benefits of AI implementation in the road sector (see Figure C.20). Time savings emerged as a standout benefit, with many respondents rating the impact as high or medium, reflecting AI’s potential to streamline processes and improve operational efficiency. Similarly, asset management and infrastructure inspection were viewed as key areas where AI is expected to deliver substantial value through better resource allocation and enhanced accuracy.

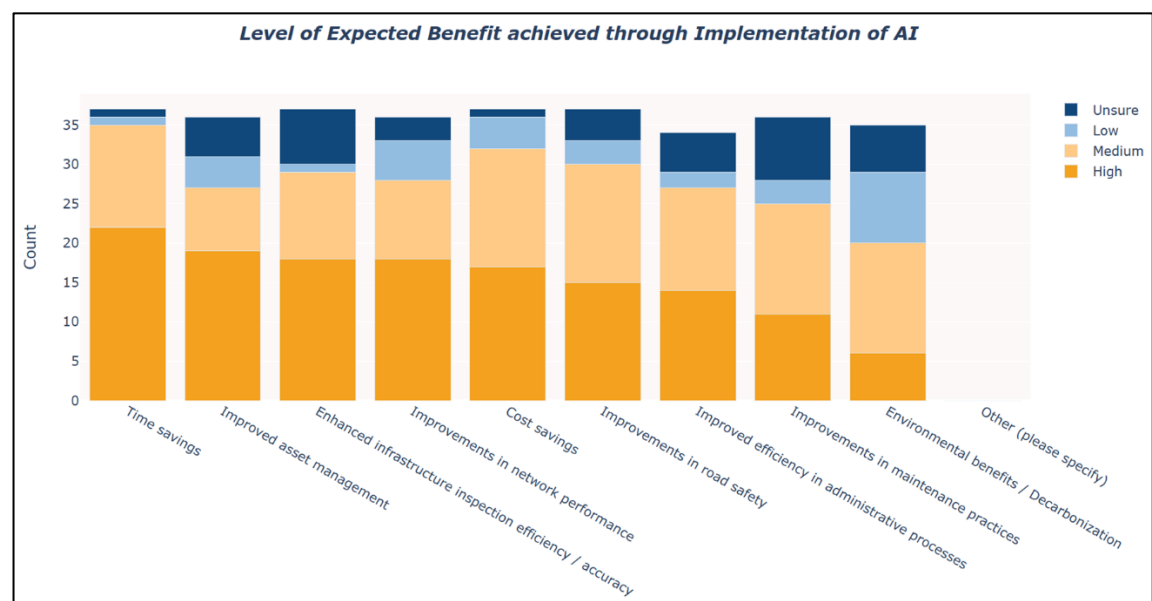


Figure C.20: Q20. You have indicated that your organisation plans to introduce/use AI technology by 2030. In your opinion, what are the expected benefits of the proposed introduction of AI technologies? If you expect to achieve benefits other than those listed below, please use the "Other" option to provide details. You may ignore/skip any items which are not relevant to you.

Cost savings and improvements in network performance were also widely recognised, with respondents anticipating AI’s role in optimising operations and reducing expenses. Road safety and maintenance practices similarly received positive expectations, underpinned by AI’s predictive capabilities and real-time monitoring. However, benefits in environmental sustainability and administrative efficiency received more cautious ratings, with several respondents unsure about AI’s impact in these areas. This suggests that while AI’s role in operational tasks is well understood, its potential in sustainability and non-operational areas remains underexplored.

The survey results for Q21 provide an overview of current AI-related projects or pilot studies in the road sector (see Figure C.21). Road operations, traffic management, and incident detection emerged as the most prominent focus, accounting for 35% of responses. This highlights the widespread use of AI to improve traffic flow and real-time decision-making.

Infrastructure inspection or monitoring followed, representing 25% of projects, reflecting the importance of AI in enhancing efficiency and accuracy in assessing road conditions and infrastructure health. Planning, feasibility studies, route selection, and project appraisal accounted for 10%, suggesting a growing interest in AI for long-term project development and decision-making. The “Other” category, making up 30%, encompassed diverse applications such as administrative functions, data analysis, and AI-driven reporting tools, showcasing the broad potential of AI in addressing varied organisational needs.

Q21 was posed to gain insight into current AI pilot studies or projects that respondents are involved in. The responses to this question are again in line with what has been viewed in the literature review and case studies sections of this report. Both infrastructure inspection and monitoring as well as traffic management or road operations are the most common activities present in the results for this question.

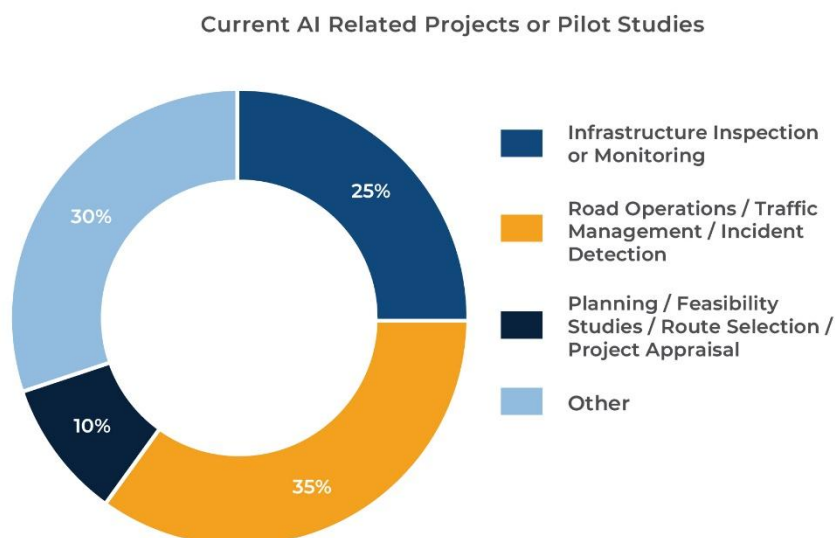


Figure C.21: Q21. Please describe any AI-related projects or pilot studies your organisation is involved in, including links to relevant websites, literature, or reports. If none, leave this question blank. Limit your response to 100 words.

The survey results for Q22 highlight anticipated future AI-related projects or pilot studies in the road sector (see Figure C.22). The “Other” category dominates with 40%, includes road safety, road design and many more road related activities.

Road operations, traffic management, and incident detection follow at 27%, showcasing ongoing interest in leveraging AI to enhance real-time traffic control and improve safety measures. Infrastructure inspection and maintenance accounts for 20%, emphasising the growing reliance on AI for efficient infrastructure management and predictive maintenance. Asset management, making up 13%, reflects its steady importance in optimising resource use and extending asset lifespans.

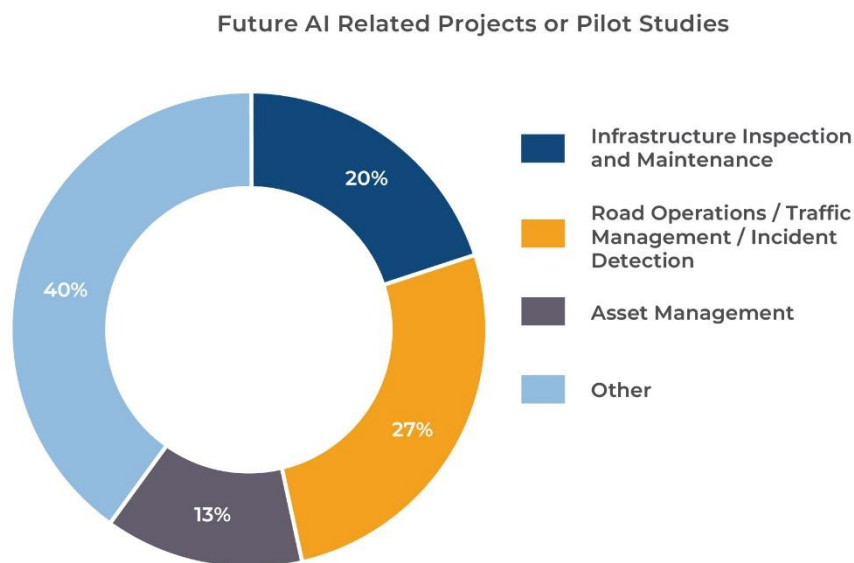


Figure C.22: Q22. Please outline any AI-related pilot projects your organisation plans to undertake by 2030. If none, leave this question blank. Limit your response to 100 words.

The survey results highlight significant uncertainty and inconsistency regarding the presence of legislation, regulations, or policies for AI implementation in the road sector. Figure C.23 and Figure C.24 illustrate responses to Q23 and Q24, where participants were asked whether they were required to adhere to any specific legislative or regulatory frameworks. The majority of respondents - 22 individuals - indicated they were unsure about the existence of such requirements, reflecting a lack of clarity and awareness globally. 16 respondents stated that they were required to follow specific guidelines, while 14 respondents confirmed that no such requirements were in place for their organisations. For those who acknowledged the presence of legislative or regulatory requirements (Figure C.24), references were made to the EU AI Act and other country-specific or internal policies. These findings suggest that while certain regions, particularly the EU, have begun to formalise AI regulations, this is not yet a universal trend.

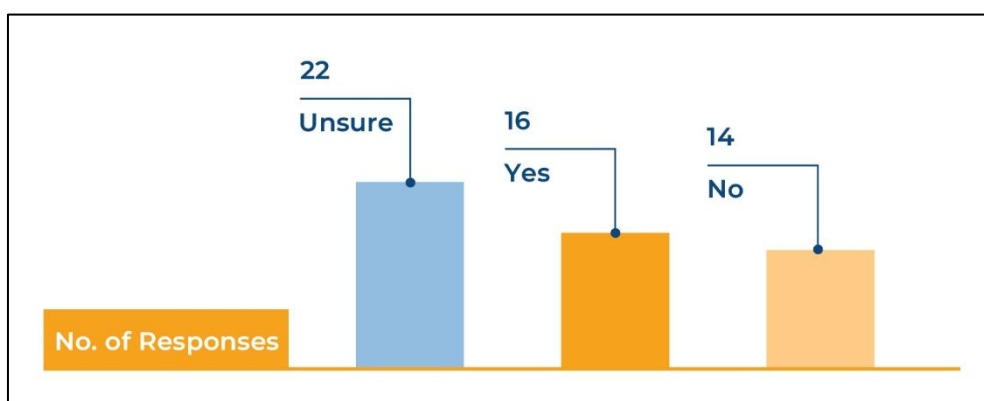


Figure C.23: Q23. With respect to any AI-based technologies, does your organisation follow any specific legislation, regulations, policies or practices?

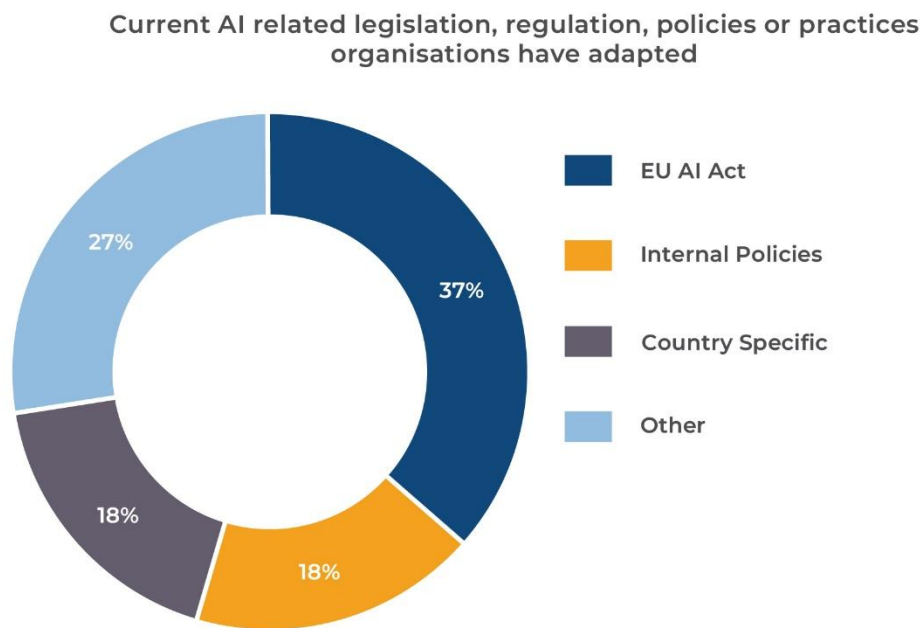


Figure C.24: Q24. Please describe/ name any AI legislation, regulations, policies or practices that your organisation has adopted. Please limit your answer to 100 words.

In Q25, respondents were asked whether their organisations plan to adopt any policies or practices to comply with AI legislation. The results, shown below, highlight that the overwhelming majority - 38 respondents -selected “Unsure”, while only 12 respondents confirmed plans to adopt such measures. Notably, no respondents indicated that their organisations definitively have no plans in this regard.

These findings underline the significant uncertainty surrounding AI regulation and legislation, particularly in the road sector. This ambiguity is likely tied to the evolving nature of AI legislation globally and the lack of clear, consistent guidance for organisations. Furthermore, the uncertainty reflects broader industry challenges in predicting how AI governance will develop and the extent to which organisations will be required to adapt by 2030.

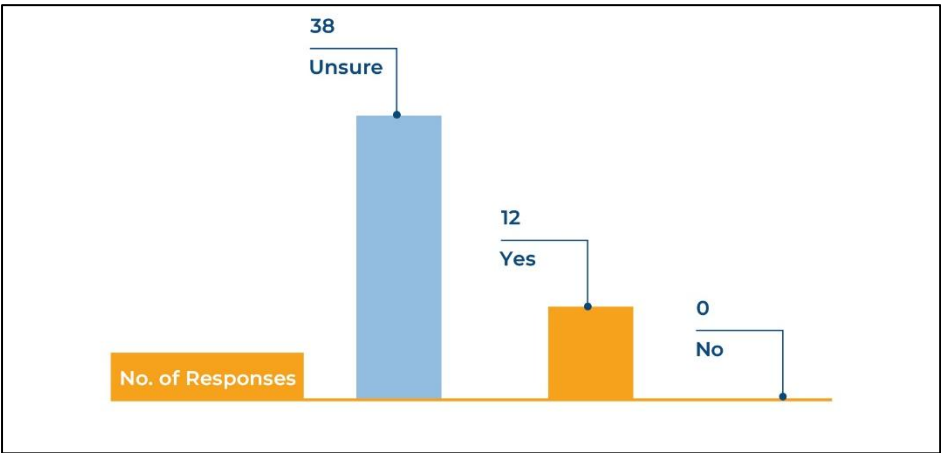


Figure C.25: Q25. With respect to any AI-based technologies, does your organisation plan to adopt any new policies or practices from now to 2030 to comply with AI legislation?

The survey results for Q26 provide insight into the types of AI-related legislation, regulations, policies, or practices that organisations have adopted. As shown in the chart, Figure C.26, 50% of respondents reported adhering to country-specific regulations, making this the most prevalent approach. This highlights the reliance on regional frameworks to guide AI implementation.

The EU AI Act accounted for 25% of responses, reflecting its significant influence as one of the first comprehensive legislative efforts to govern AI. This result underscores the leadership role of the EU in setting standards for AI governance. Internal policies, adopted by 12.5% of respondents, demonstrate that some organisations are proactively creating their own guidelines to ensure compliance and responsible AI use. However, this relatively low percentage suggests that most organisations rely on external frameworks for direction.

Finally, the “Other” category made up 12.5% of responses, noted that there are no current regulations but any future legislative measures, once enacted, will be applied as required.

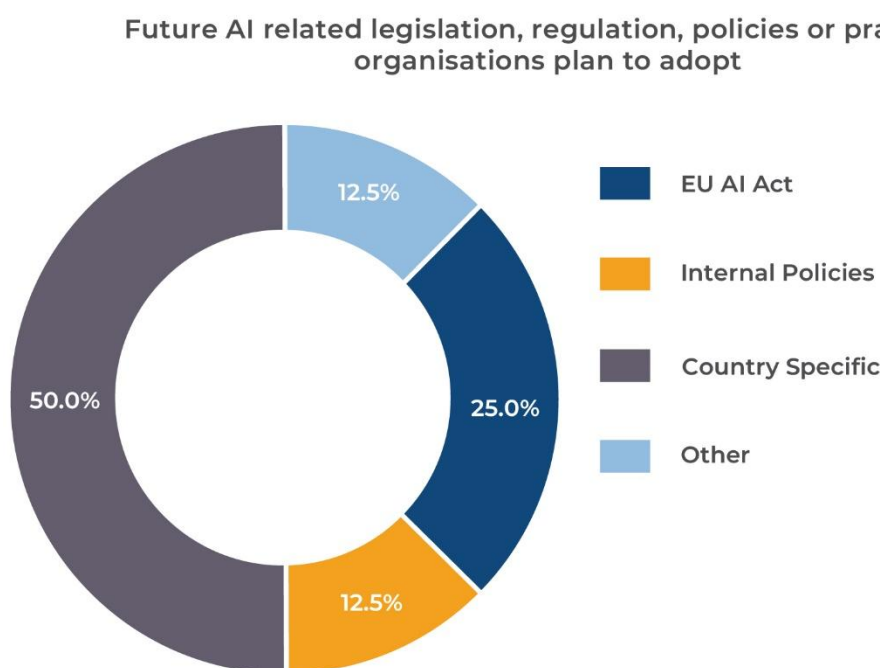


Figure C.26: Q26. Please describe any legislation, regulations, policies, or practices that your organisation plans to adopt for the use of AI from now until 2030. Please limit your answer to 100 words.

The survey results for Q27 reveal a range of challenges and barriers organisations face in adopting AI within the road sector, with variations across HICs, UMICs, and Lower MICs+LICs (see Figure C.27). These findings highlight both universal concerns and region-specific issues.

Data issues, including privacy, cybersecurity, and data-sharing limitations, were among the most significant barriers, particularly in HICs and UMICs. These countries, which are further along in AI adoption, expressed high concern over the reliability and security of data, underscoring its critical role in effective AI implementation. A lack of skilled workforce was a predominant challenge in Lower MICs+LICs, where high ratings reflected significant gaps in AI expertise. This issue highlights the need for targeted training and capacity-building initiatives in these regions to ensure successful adoption.

Technical issues and a lack of supporting infrastructure were noted across all income groups, but the concern was particularly pronounced in Lower MICs+LICs. Many respondents pointed to insufficient infrastructure, such as ITS equipment, as a major hurdle, while HICs and UMICs emphasised the technical complexities of integrating AI systems. Financial barriers and prohibitive costs were another significant concern, especially in Lower MICs, where limited resources make it difficult to fund large-scale AI initiatives. In contrast, HICs and UMICs reported fewer concerns in this area, likely due to better access to funding and resources.

Legal and regulatory challenges were highlighted as a medium-to-high concern across all regions. The lack of clear, consistent legislation governing AI creates uncertainty and complicates compliance efforts, particularly as organisations navigate rapidly evolving technologies. Trust in AI systems emerged as a critical barrier, especially in UMICs. Concerns about reliability, transparency, and potential biases in AI decision-making reflect the need to build confidence in these systems through improved design and communication.

Resistance to organisational change was also a notable challenge, particularly in Lower MICs+LICs. Adapting to new AI-driven approaches requires significant cultural and structural adjustments, which can be difficult in regions where organisational inertia may be more deeply entrenched. Lastly, fear of job replacement was most pronounced in Lower MICs+LICs, where the reliance on manual labour is greater, and the introduction of AI raises concerns about workforce displacement. This underscores the importance of addressing these fears through transparent communication and upskilling opportunities.

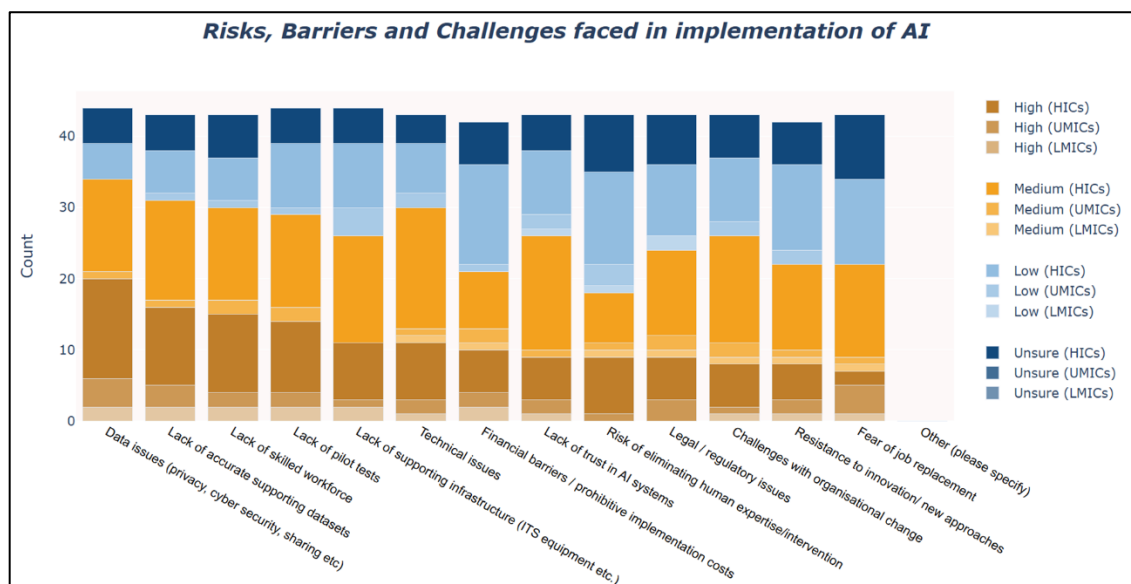


Figure C.27: Q27. What risks, barriers and challenges have you or your organisation faced in implementing AI (if any)? Please select any that apply and indicate the level of difficulty/risk. For risks, barriers or challenges other than those listed below, please use the "Other" option to provide details. You may ignore/skip any items which are not relevant to you.

The survey results for Q28 reveal how organisations mitigated risks and overcame challenges or barriers associated with AI implementation in the road sector (see Figure C.28). The responses, summarised in the chart, highlight a variety of approaches.

Training and workforce development and research activities, such as cost-benefit and risk analysis, were each employed by 25% of respondents. These strategies emphasise the importance of equipping staff with the necessary skills and knowledge while using thorough analysis to guide decision-making and address uncertainties. Pilot studies were cited by 12% of respondents as a method for overcoming barriers. Pilot projects allow organisations to test AI applications in controlled environments, helping them identify and address issues before wider adoption.

The “Other” category, representing 38% of responses, encompassed a range of alternative approaches, through government mechanisms such as access to technical resource. Organisations have also noted that continuous direct contact with technological providers during the implementation process can help mitigate the likelihood of any delays.

How Risks were Mitigated and Challenges/Barriers were Overcome

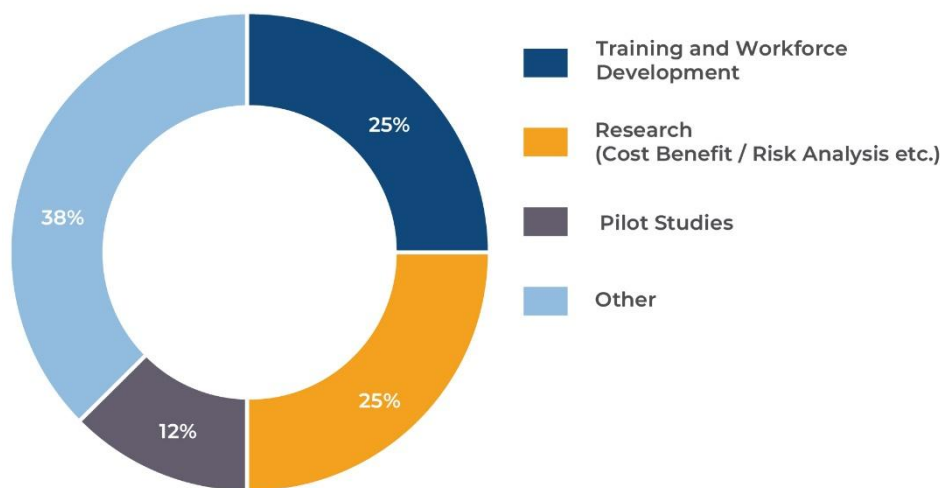


Figure C.28: Q28. If you answered the previous question, please describe if/how these risks were mitigated, or the barriers/challenges were overcome.

The final question posed to the relevant stakeholders in this survey was in relation to any additional comments and feedback that respondents may have in relation to AI implementation in the road sector. This additional feedback received from the respondents provided varied comments, some of which have been addressed already in the stakeholder engagement. One comment from a LIC detailed some of the key factors that will influence AI implementation in the road sector. This included adequate training and upskilling, ensuring accurate road data, prioritising investment in AI infrastructure and developing clear guidelines for responsible use of AI. Other comments highlighted the importance of regulation and governance and how it may impact AI adoption. Multiple other applications of AI were noted in the responses to this question including the use of AI in bridge inspection using drones and to enhance administrative work.

INTERVIEWS

The survey analysis identified key road sector stakeholders, who were invited to interviews exploring AI adoption, challenges, and opportunities across different contexts. The interviews focused on three themes: (1) AI technology pilots, (2) AI adoption and challenges in HICs, and (3) opportunities and barriers in the road sector in LMICs. ROD conducted 8 interviews with 11

stakeholders from 7 countries, capturing a diverse range of global perspectives. The structured question framework ensured relevance to each stakeholder’s context, facilitating meaningful discussions on AI applications. A semi-structured approach was adopted, with interview questions shared in advance to support participant preparation. These questions, provided in Appendix D, guided discussions and enabled the collection of detailed, actionable insights.

The following sections outline the key findings from the interviews and Table C.2 provides an overview of the interviews carried out.

9.1.21. Activities in the road sector

Figure C.29 summarises different activities for which interviewees have experience working with or have implemented AI technologies to improve their operations. Road safety was highlighted as a key concern in the survey process, particularly in LMICs where the vast majority of road fatalities and serious injuries occur. In order to reflect this priority area, ROD conducted interviews with a number of stakeholders working in road safety and traffic operations, along with others who were focused infrastructure inspection and asset management, which was also identified as a key area of importance from the surveys and literature review.

Table C.2: Overview of interviews.

Organisation name	Country	No. of Interviewees	Income Class
Lima Expresa (Lanternn)	Peru	2	UMIC
iRASTE	India	1	LowerMIC
VíaSegura International Road Assessment Programm (iRAP)	United Kingdom	1	HIC
VíaSegura Inter-American Development Bank (IDB)	Various countries (Latin America and the Caribbean)	2	Various
Transport Research Laboratory (TRL)	United Kingdom	1	HIC
Uganda NRA (UNRA)	Uganda	1	LIC
Danish Roads Directorate (DRD)	Denmark	1	HIC
Transport for NSW (TfNSW)	Australia	2	HIC

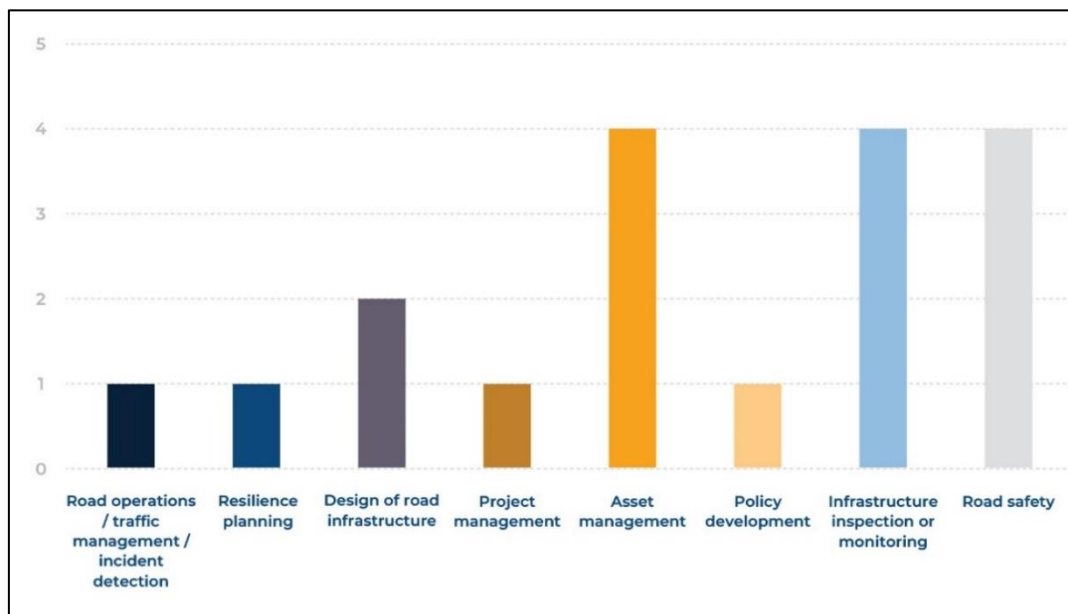


Figure C.29: Different activities for which interviewees are involved or have implemented AI technologies

9.1.22. Key benefits achieved through AI implementation

Figure C.30 provides an overview of the types of benefits achieved, as noted by interviewees who have implemented AI in their various activities in the road sector. The reported benefits were closely aligned with the areas in which the technologies were implemented and included improvements in road safety, and time or cost savings representing the most significant benefits, with 30% of interviewees noting improvements in road safety or time savings. Cost savings were also regularly reported along with benefits in inspection or monitoring of infrastructure, or overall improvements in operational performance of the road network.

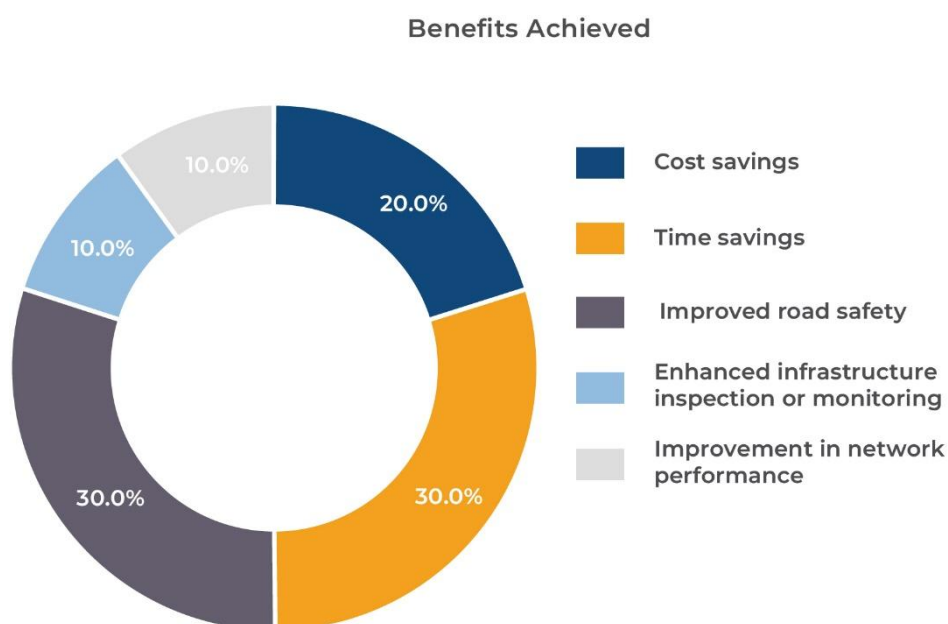


Figure C.30: Key benefits noted by interviewees in their AI implementation

9.1.23. Key challenges faced

Multiple challenges associated with AI implementation were identified by interviewees. Figure C.31 presents a breakdown of the challenges noted by interviewees during their adoption or wider adoption of AI technologies. The most commonly cited issues faced by interviewees related to the lack of skilled workforce, financial barriers and data-related issues, which each accounted for 20% of the identified challenges. Training of workers and adapting to procedural change was an apparent issue across HICs and LMICs, this training is a requirement as processes transition towards greater degrees of automation. This change is closely reflected by resistance to change amongst the workforce which was again, regularly cited as a primary challenge, and very often linked to a fear of job replacement.

9.1.24. Other comments (HICs)

The interviews also highlighted various considerations which must be taken into account when implementing AI. A discussion was held during one of the interviews from a HIC in relation to the direction which NRAs or other ROs might take as part of the transition to AI. Organisations may choose to invest in third-party AI systems delivered through Software as a Service (SaaS) models or they may choose to invest in developing proprietary AI software in-house. This decision, which may be governed by an overarching organizational preference, has significant implications for scalability, control and long-term cost-efficiency. SaaS models offer ready-to-deploy solutions with lower initial setup costs, while in-house proprietary AI software could allow for greater customisation and adaptability which could cater more specifically to certain organisations' requirements.

There are multiple other factors that must be considered when determining the most suitable approach to this decision such as the requirement for technical expertise, complexity of the application, data security concerns, cost and budget constraints among others. Incident detection systems for example Lanternn by Valerann operate with a SaaS model which provides multiple benefits for road authorities that may not be possible if a similar system was attempted to have been developed in-house. An example of an in-house software that has been developed which has already been noted in the literature review is the SCATS tool developed in Sydney to optimise traffic flow and reduce congestion. Although now it has been commercialised and is available worldwide for licensing the system was originally developed specifically for Sydney's traffic authority. The in-house system was developed to allow for high customisation capabilities which would be specific to the Sydney road network.

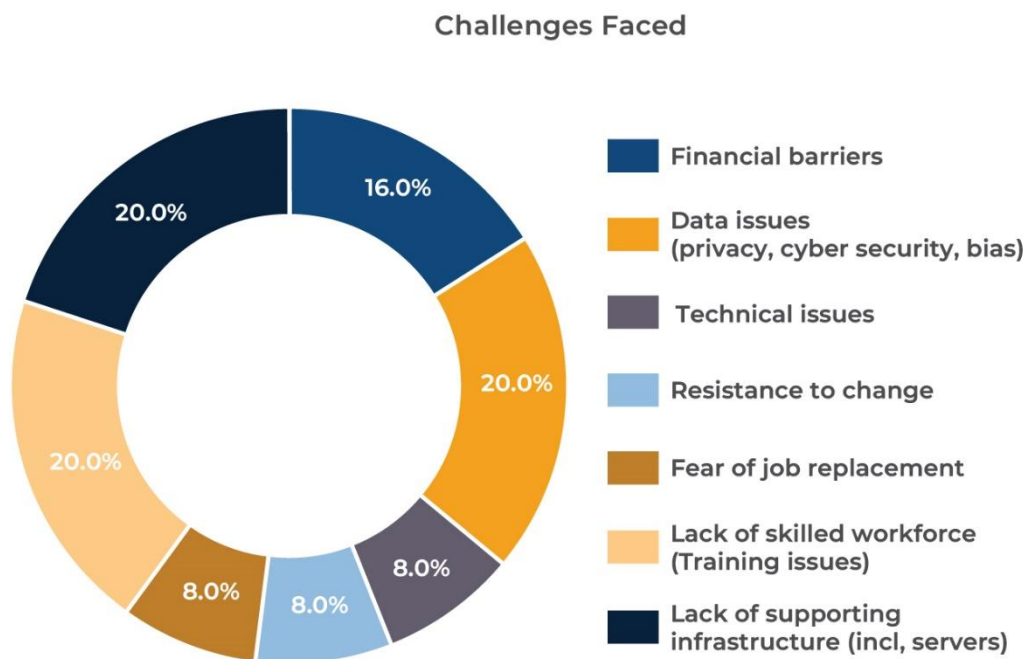


Figure C.31: Challenges faced by interviewees during the implementation of AI-based technologies.

9.1.25. Other comments (LMICs)

Another key consideration which was noted by an interviewee from a LIC was the requirement for change in culture in relation to the adoption of AI technologies. Leaders within governments and organisations have the influence to bring this change in culture, by need to be guided by technical expertise and an ability to demonstrate the benefits. This consideration is indeed relevant, to some extent, in both HICs and LMICs. Key pilot projects, working on some of the most pressing issues such as road safety, can be used to highlight the benefits associated with the novel technologies. This can transform the innovation culture and help lead to a broader acceptance of AI amongst leaders.

Sustainability and environmental or climate-related issues are a key concern globally and are of paramount concern for LMICs which may not be equipped to tackle the effects of climate change. Infrastructure resilience is a crucial factor which heavily dictates the ability of countries to deal with climate-related events and many road authorities direct their attention on allocating resources to these areas.

In relation to asset management or infrastructure inspection or monitoring and due to the limited resources available in LMICs there must be strategies in place to optimise data collection processes. The first step in this process is to determine the correct data to collect and where to allocate resources. A key concern for LMICs associated with this process is when foreign consultants, who are often required to fill gaps in local technical expertise, don't understand local geography or community needs. Local knowledge can be crucial in optimising the effectiveness of data collection processes to improve the efficiency of AI systems.

APPENDIX D: INTERVIEW QUESTIONS

INTERVIEW QUESTIONS FOCUSED ON CASE STUDIES

General Notes

The interview should not last more than 1 hour.

Introduction/Background

The purpose of this interview is to allow us to gain an understanding of AI-based technologies which are being used in the roads sector.

The results will inform a final report for [PIARC](#) (World Road Association), which will summarise current and future AI technologies in the road sector. The final report will be publicly available and will include recommendations on AI adoption for organisations in the road sector globally.

In order to allow us to obtain as much information as possible from the interview we would like to record the conversation. Would you be willing to give us permission to record this interview?

Prior to publishing any information in the final report, we will share a version of the text for approval before it is published.

What is your (or your organisation's) scope in relation to road infrastructure?

What is your background? (get a brief summary of the interviewee's areas of experience/expertise)

Open-Ended Questions (Allowing for Interaction/Discussion with Interviewers)

1. Please provide a general overview of the pilot/trial of the AI technology which has been adopted? As part of this we would be interested to get insight into the following:
 - a. What was the previous workflow before the technology was implemented?
 - b. What were the primary challenges / difficulties?
 - c. Why was the particular AI/technology type chosen & what was the primary motivation?
 - d. Where was the technology deployed? (location, geographical extent etc.)
2. When was the technology piloted/implemented, and for how long?
3. Please describe the organisations/people who were involved in the pilot?
 - a. Was it done primarily in-house?
 - b. Were contractors/consultants involved/required?
 - c. Were there specialist technology/equipment providers involved/required?
4. Was it necessary to purchase/procure any systems/hardware? If so, what was the procurement process?
5. What were the main benefits achieved (if any) by using the new technology? Was it possible to quantify any of these benefits with specific metrics, and if so, how was this done and what were the improvements?

6. Were there any challenges encountered or any barriers which needed to be overcome when adopting the technology? If so, how were they addressed and what recommendations would you have for other organizations who may experience similar challenges? Barriers/challenges may include some of the following:
 - a. People / staffing (lack of expertise, resistance to change, lack of resources)
 - b. Technical
 - c. Lack of supporting infrastructure (ITS equipment, data centres, communications)
 - d. Difficulties with procedural change or identification of new roles/staffing structures
 - e. Etc.
7. Where possible, we would like to get an idea of the costs associated with implementing AI-based technologies. Can you elaborate on any costs associated with the pilot/trial?
 - a. Upfront hardware/software costs
 - b. Costs associated with consultants / specialists
 - c. Costs associated with hiring of additional staff, or training of existing staff
 - d. Ongoing maintenance / support costs (software/hardware)
 - e. Costs associated with purchasing, management or storage of data
 - f. Etc.
8. There is often a concern relating to the introduction of 'risks' by adopting AI-based technologies. Did you consider that implementing AI-based technology may introduce some risks? If so, did you introduce any measures to mitigate/eliminate these risks, and did the risks actually materialise? Typical concerns arise in relation to the following:
 - a. Data security/privacy
 - b. Cyber attack, particularly in relation to transport infrastructure
 - c. Fear of job replacement amongst staff (and associated resistance to change)
 - d. Reliability/accuracy of AI systems / data
 - e. Etc.
9. AI technologies are quickly evolving, and in many countries there are no specific legal requirements or regulations relating to use of AI in the roads sector. Were you required to comply with any specific legal/regulatory requirements?
10. If you were to embark on the same project again, what would you do differently?

INTERVIEW QUESTIONS FOR GENERAL INTERVIEWS (HICs)

General Notes

The interview should not last more than 1 hour.

Introduction/Background

The purpose of this interview is to gain insights into the current challenges faced by organisations in the road sector, with a focus on adoption of AI technologies.

The results will inform a final report for [PIARC](#) (World Road Association), summarising the state of AI readiness in the road sector and providing recommendations for future adoption. The final report will be publicly available and will include strategies for organisations in the road sector globally.

In order to obtain as much information as possible from the interview, we would like to record the conversation. Would you be willing to give us permission to record this interview?

What is your (or your organisation's) scope in relation to road infrastructure?

What is your background? (get a brief summary of the interviewee's areas of experience/expertise)

Open-Ended Questions (Allowing for Interaction/Discussion with Interviewers)

1. Can you describe the current state of road infrastructure management in your organisation?
 - a. What are the main challenges or difficulties you face in your day-to-day operations?
 - b. How do these challenges impact your overall effectiveness and efficiency?
2. What are your thoughts on the potential role of AI in addressing the challenges you've identified?
 - a. What specific problems do you believe AI could help solve in your current context?
 - b. Are there particular AI applications or technologies that you find most promising for the road sector?
3. Where/how could the biggest impact be made to improve the following:
 - a. Design/planning of new road construction.
 - b. Construction techniques/materials.
 - c. Road safety / incident reduction.
 - d. Inspection/maintenance/repair of existing infrastructure.
 - e. Sustainability/climate-related adaptation.
4. What barriers do you perceive in adopting AI technologies within your organisation?
 - a. Do you face challenges related to funding, skills, or technology infrastructure?
 - b. How do these barriers affect your willingness or ability to pursue AI solutions?
5. Have you engaged with any initiatives or discussions regarding AI adoption in the road sector?

- a. If yes, can you share your experiences and insights from these discussions?
 - b. If no, what factors have prevented you from engaging in such initiatives?
6. In your opinion, what would be necessary to facilitate AI adoption in your organisation?
 - a. Are there specific resources, training, or policy changes you believe are required?
 - b. How can stakeholders (government, private sector, international organisations) support your organisation in this regard?
7. What concerns do you have regarding the implementation of AI technologies?
 - a. Are there specific risks related to data privacy, job displacement, or technical reliability that you are particularly concerned about?
 - b. How do you think these concerns could be addressed?
8. How do you perceive the role of regulatory frameworks in AI adoption?
 - a. Do you believe existing regulations are adequate, or do they present obstacles to AI implementation?
 - b. What regulatory changes do you think are necessary to facilitate AI adoption in your sector?
9. If your organisation were to embark on an AI initiative in the future, what steps do you believe would be crucial to ensure its success?
 - a. What key stakeholders should be involved in the process?
 - b. Are there specific pilot projects or partnerships you would consider pursuing?
10. Can you describe any current efforts or strategies in your organisation aimed at preparing for AI adoption?
 - a. What specific initiatives, if any, are you currently exploring?
 - b. How are you planning to build the necessary skills and knowledge among staff?
11. Looking ahead, what are your long-term goals for your organisation concerning AI and road infrastructure?
 - a. What is your vision for the future, and how do you see AI fitting into that vision?
 - b. What steps do you think are essential to achieve that vision in the coming years?

INTERVIEW QUESTIONS FOR GENERAL INTERVIEWS (LMICs)

General Notes

The interview should not last more than 1 hour.

Introduction/Background

The purpose of this interview is to gain insights into the current challenges faced by organisations in the road sector, with a focus on the adoption of AI technologies.

The results will inform a final report for [PIARC](#) (World Road Association), summarising the state of AI readiness in the road sector and providing recommendations for future adoption. The final report will be publicly available and will include strategies for organisations in the road sector globally.

In order to obtain as much information as possible from the interview, we would like to record the conversation. Would you be willing to give us permission to record this interview?

What is your (or your organisation's) scope in relation to road infrastructure?

What is your background? (get a brief summary of the interviewee's areas of experience/expertise)

Open-Ended Questions (Allowing for Interaction/Discussion with Interviewers)

1. Can you describe the current state of road infrastructure management in your country/organisation?
 - a. What are the main challenges or difficulties you face in your day-to-day operations?
 - b. How do these challenges impact your overall effectiveness and efficiency?
2. Is there any data collected systematically for use in road operations, maintenance etc.?
 - a. Information / statistics around traffic incidents?
 - b. Infrastructure condition data?
 - c. General asset data / inventories (type, location, geometry etc. etc.)?
3. Are there formal procedures in place for collection or management of any such data sets (inspection data, incident details, details of existing infrastructure)?
4. What are your thoughts on the potential role of AI in addressing the challenges you've identified?
 - a. What specific problems do you believe AI could help solve in your current context?
 - b. Are there particular AI applications or technologies that you find most promising for the road sector?
5. Where/how could the biggest impact be made to improve the following:
 - a. Design/planning of new road construction.
 - b. Construction techniques/materials.
 - c. Road safety / incident reduction.
 - d. Inspection/maintenance/repair of existing infrastructure.

- e. Sustainability/climate-related adaptation.
- 6. What level of technology is used in the roads sector and where have the biggest or most impactful developments been seen in recent years?
- 7. What level of emphasis is put on sustainability, environmental or climate-related issues for roads?
- 8. What barriers do you perceive in adopting AI technologies within your organisation?
 - a. Do you face challenges related to funding, skills, or technology infrastructure?
 - b. How do these barriers affect your willingness or ability to pursue AI solutions?
- 9. Have you engaged with any initiatives or discussions regarding AI adoption in the road sector?
 - a. If yes, can you share your experiences and insights from these discussions?
 - b. If no, what factors have prevented you from engaging in such initiatives?
- 10. In your opinion, what would be necessary to facilitate AI adoption in your organisation?
 - a. Are there specific resources, training, or policy changes you believe are required?
 - b. How can stakeholders (government, private sector, international organisations) support your organisation in this regard?
- 11. What concerns do you have regarding the implementation of AI technologies?
 - a. Are there specific risks related to data privacy, job displacement, or technical reliability that you are particularly concerned about?
 - b. How do you think these concerns could be addressed?
- 12. How do you perceive the role of regulatory frameworks in AI adoption?
 - a. Do you believe existing regulations are adequate, or do they present obstacles to AI implementation?
 - b. What regulatory changes do you think are necessary to facilitate AI adoption in your sector?
- 13. If your organisation were to embark on an AI initiative in the future, what steps do you believe would be crucial to ensure its success?
 - a. What key stakeholders should be involved in the process?
 - b. Are there specific pilot projects or partnerships you would consider pursuing?
- 14. Can you describe any current efforts or strategies in your organisation aimed at preparing for AI adoption?
 - a. What specific initiatives, if any, are you currently exploring?
 - b. How are you planning to build the necessary skills and knowledge among staff?
- 15. Looking ahead, what are your long-term goals for your organisation concerning AI and road infrastructure?

- a. What is your vision for the future, and how do you see AI fitting into that vision?
- b. What steps do you think are essential to achieve that vision in the coming years?

APPENDIX E: CASE STUDIES: DETAILED DESCRIPTIONS

This section presents selected case studies illustrating the practical application of AI technologies in key areas identified in the literature review. These case studies highlight various AI technologies, their benefits, challenges, costs, and implementation effectiveness. The first two case studies are based on data from the INFRACOMS project (Fjendbo et al., 2023a, 2023b). Following discussions with INFRACOMS representatives, no concerns were raised regarding the use of this information in the recommendations and case studies sections of this report. It is noted that although these case studies aim to provide a representative view of the common applications of AI technology in the road sector, considering a global spread and countries of differing levels of economic development, there are many other examples globally which are not included in this report.

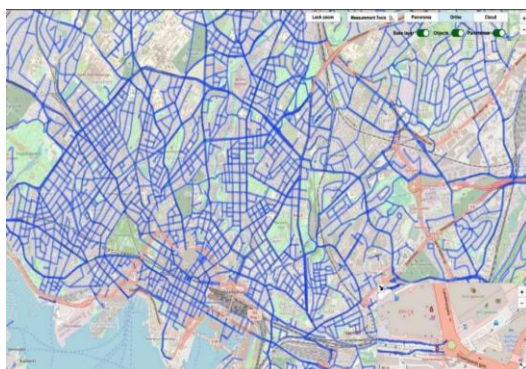
EYEVİ PLATFORM - DIGITALISATION OF DEFECTS ON OSLO'S URBAN ROAD NETWORK

Case study description

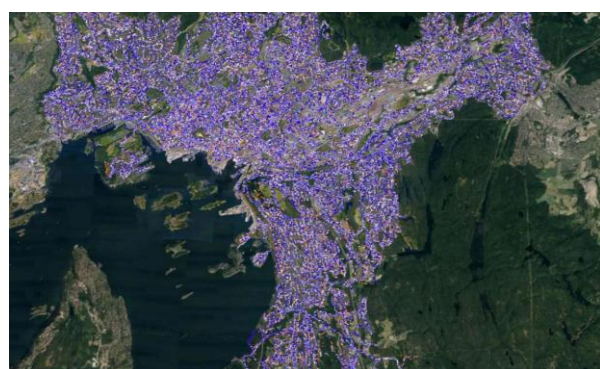
This case study details the City of Oslo's experience in the digitalisation of road defects on the urban road network. This platform enhanced decision-making processes in Oslo by providing objective, data-driven insights. A total length of 1300km of urban roads were analysed with 1.3 million defects found on the road network. It helped address previous data gaps and significantly improved the budget allocation process.

The city of Oslo wanted to create a road masterplan outlining maintenance needs for its road network. The goal of this was to develop a plan that could prioritise maintenance actions objectively, reducing the reliance on personal opinions. The aim of this was to ensure a more data-driven approach to asset management and asset quality. Numerous steps were taken to create a digital overview of the entire Oslo municipality's road network, these steps are outlined below.

A tender was issued by the city, allowing consultants to leverage the technology of their choice to gather the required data to create the road masterplan. The city defined essential elements and additional ones for consideration within a fixed budget of 2.8 million NOK (approx. €236,000) in 2021. The tender was also published in the EU market.



(a)



(b)

Figure E.1: (a) Map of Oslo city road network that was assessed (b) 1.3 million road defects highlighted on Oslo city road network.

Technology description

The EyeVi system includes a vehicle-mounted 360° panoramic camera, LiDAR scanner, and a navigation system sensor. The system can be setup on most vehicles with ease. Data is collected by the system as the vehicle drives across the road network. The system captures images every 3 metres and has a data gathering speed between 50-70km/h, storing data on an SSD in a field computer. The EyeVi Data Capture tool is fieldwork software that has been developed to help effective data collection. It manages the collection of the GNSS/INS data, LiDAR data, and raw panoramic camera imagery, providing real-time feedback on data quality and allowing drivers to start and stop data collection. The captured data is processed using data production software to generate panoramic images, high definition orthophotos and full coverage point clouds.

Table E.1: AI Capabilities of the EyeVi system.

AI Capabilities	Description
Road defects	The AI processing tool identifies road defects such as cracks, network cracks, patches etc. using ortho imagery.
Footway defects	AI can detect defects on pavements designed for pedestrians, with cracks in sidewalk plates and other anomalies.
Road signage	360° panoramic images are used to detect roadside traffic signs along with their type.
Point cloud classification	The AI feature detection can distinguish different objects, differentiating between ground and structures like buildings, trees and vehicles, among other things.

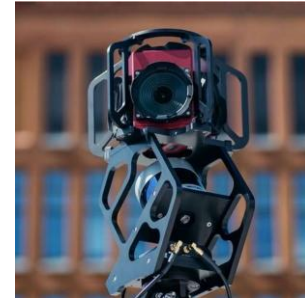
The EyeVi Data Processing Software is an automated cloud-based data processing tool that takes the raw sensor input from EyeVi Data Capture. This produces 360°panoramic images which offer a comprehensive visual perspective of the environment, it also provides high definition orthophotos from the panoramic images with detailed images of the road surface with resolutions of 0.5cm and the software creates point clouds which are 3D representations of the captured environment.



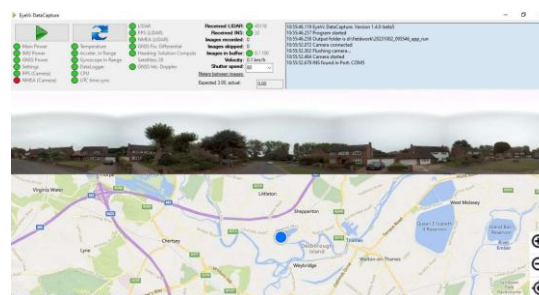
(a)



(b)



(c)



(d)

Figure E.2: (a)-(c) EyeVi hardware and system setup & (d) EyeVi Data Capture tool interface.

The data analysis is performed using AI processing which can also work on standard 3rd party datasets, if the panoramas, orthophotos and/or point clouds are of good quality. The source of these datasets does not matter as the AI feature detection will work for all necessary good quality datasets. The capabilities of the AI detection system can be seen in Figure E.2.

Figure E.3 displays a number of the above AI capabilities of the EyeVi system.



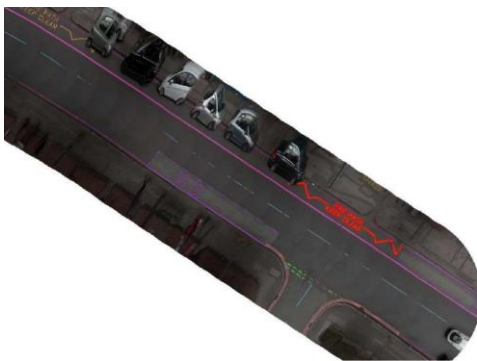
(a)



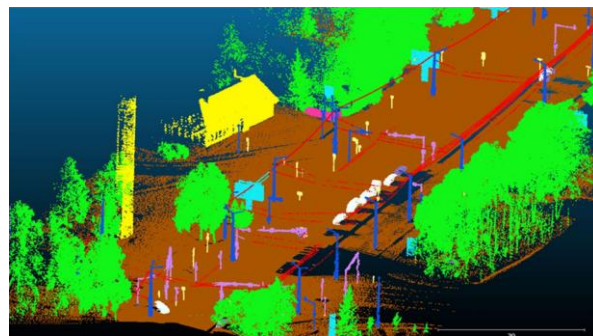
(b)



(c)



(d)



(e)

Figure E.3: (a) AI feature detection to identify road defects (b) Sidewalk defects identified with AI processing (c) Road signage detected using the AI feature detection (d) Detection of road markings (e) AI differentiating between objects.

Benefits

The city of Oslo obtained several benefits as a result of implementing the EyeVi technology platform.

Critical gaps in road network maintenance data were closed and it provided a relatively complete and up to date documentation of the road network in the city. These gaps were a result of a previous approach which suffered from incomplete and outdated information.

The technology provided a visual representation of the road condition, overcoming limitations of the previous system which improved the data representation.

The system can accurately detect and capture 34 features including the road defects cracking, network cracking, edge defects, potholes and weathering.

This new system enabled objective data collection which contrasts to the previous data collection efforts which were incomplete and subjective. Previously, decisions were made based on personal opinions due to a lack of complete data. The technology now helps decision-makers with data-backed insights, leading to more informed and less objective decisions.

The adoption of the technology allowed for better budgeting based on the objective data and documented needs of the public. Financial planning and resource allocation was improved, and the improved maintenance planning associated with the data collected meant that cost savings were attainable due to the reduced reliance on costly evaluations from consultants.

Potential risk, barriers and implementation challenges

There were several risks, challenges and barriers associated with the implementation of the EyeVi technology platform by the city of Oslo. They are detailed in Table E.2.

Overall, while the technology has delivered significant benefits, there is ongoing work to address remaining limitations and explore ways for enhancing data completeness and quality.

Cost

There were no costs for purchasing the systems or equipment, only data was procured. Accurate information on this data procurement is unknown, however, it is understood that the initial budget for the project was approximately €236,000.

Asset management will be financially impacted by the use of this technology. In addition to giving information about the location of damages, it also enables more accurate road maintenance forecasting. Consequently, the city can allocate resources more efficiently, resulting in improved cost control. Dealing with damage as soon as possible reduces expenses by preventing more extensive and expensive repairs.

Concluding remarks

In conclusion, there are a lot of benefits for the City of Oslo using the EyeVi technology platform for road inspection and monitoring. It has enabled objective data collecting, improved informed decision-making, and ensured more thorough and current documentation of the road network. The technology has improved resource allocation and efficiency through improved data analysis and representation. Challenges were handled effectively, including delays in data gathering and processing in areas with poor GNSS signals. All things considered, the implementation of the EyeVi technology platform transformed budget allocation, asset management, and decision-making in road inspection and monitoring, putting the city in a position to significantly enhance its policy choices, asset management and road infrastructure.

Table E.2: Description and solution of some of the potential barriers, risks and challenges faced.

Potential Challenge	Description	Solution
Data Collection	Issues were identified during the pilot testing phase, most notably relating to parked cars, obstructions such as construction zones, adverse weather conditions and areas with poor GNSS signals.	The city believed that road conditions in the obstructed areas would be similar to the surrounding road conditions, minimising the impact on data accuracy. Revisits were required to certain locations with poor GNSS signals.
Data analysis	Data analysis presented difficulties relating to the level of damage to specific damage groups.	This was resolved relatively easily after some discussion during the implementation process. There were still some gaps present in the data, with elements like curb stones, storm drains, and distinguishing between private and public objects not entirely covered.
Delays	The project encountered delays, taking a few weeks longer than initially planned to process the data, these delays can impact project timelines and resource allocation.	No specific details were given on the solution to these delays that were encountered.
Resistance to change and changes in workflow processes	There was resistance to change in procedures by workers in the road maintenance department as they were not enthusiastic about learning new programs and adapting to changes brought by the technology.	The (N)RA document standards were used as a foundational reference. Specific features requested by the client required certain changes to workflow procedures. Collaboration between the consultants and the city focused on configuring the technological solution to meet the city's specific requirements.
Data Migration and Testing	The collation and storage of the collected data could have posed issues for the City of Oslo.	The city employed the "Nasjonal veidatabank," a national road asset management system, which is a standard in Norway. Data migration, integrity, accuracy, and system performance were required and upheld by regularly checking if the data was collected, with quality controlled through experience and documentation.

COWI VIRTUAL INSPECTION PLATFORM - CONDITION ASSESSMENT OF FAROE BRIDGES

Case study description

This case study focuses on the implementation of the COWI virtual inspection (CVI) platform for the inspection and monitoring of the Faroe bridges in Denmark, which are under the responsibility of the Danish Road Directorate (DRD).

The Faroe bridges consist of two bridges in succession in south-east Denmark. The Northern bridge is a girder bridge connecting Zealand to Faroe. The Southern bridge is a cable-stayed bridge connecting Faroe to Falster. The CVI project on the Faroe bridges focuses on the pylons of the cable-stayed bridge.

The primary objectives of implementing the drone inspection technology were to reduce operational costs, optimise data collection efficiency, introduce automated systems for damage identification and establish a comprehensive inspection data management system.

The following points were noted in the study:

Table E.3: Overview of implementation of CVI platform in Denmark.

Point	Description
Regulatory Compliance	DRD collaborated with consultants to get an understanding of any limitations and to obtain necessary permits from the road authority.
System Design and Configuration	In cooperation with COWI, the vendor, the technological solution was configured according to DRD's specifications. To create a solution for DRD, the cloud-based COWI Virtual Inspection Platform was modified and integrated with pre-existing systems. Captured photos were made available to DRD and COWI for the purpose of defect identification and visualisation.
Pilot Testing	The pilot testing helped determine the required size and environment for the virtual inspection platform to outperform traditional methods and highlight any other potential major issues before full implementation.
Training and Change Management	COWI offered training workshops to familiarise DRD personnel with the technology and its capabilities. Change management strategies were developed to facilitate a smooth transition and address any resistance to change.
Deployment and Integration	The solution provided compatibility and data interoperability even though it wasn't directly linked into DRD's asset management system. DRD received metadata from the COWI Virtual Inspection Platform.
Data Migration and Testing	There was no data migration from the old systems to the new one. However, through testing and validation against predetermined acceptance criteria, data accuracy, integrity, and system performance were guaranteed.
Rollout and User Support	The new solution was initially rolled out for large structures with limited accessibility. Questions and concerns that came up during the rollout were appropriately addressed.

Technology description

The CVI utilises two types of images for analysis: normal day light images and thermal images. These images were all captured using a drone which was operated by professional drone pilots.

Data Collection

DRD utilised Reality Capture Model (RCM), a Virtual twin technology, for the bridge inspection. The RCM is created using photogrammetrically processed images captured with a drone which is operated by COWI's external partner and drone company WeFly. RGB imagery is captured with a DJI M300 with pixels of 1.2-7.8 mm, and thermal images are captured simultaneously with a DJI Zenmuse H20T.

The use of real time kinematic positioning (RTK) is geo reference of the pictures, helped in creating a 3D representation of the image location in real time. Typically, a surveyor establishes separate fix points on the structure for geo reference. The drones operate in a predetermined flightpath at approximately 15 m from the bridge. The flight path is determined by weather conditions, drone capability (tight spaces), light conditions, quality of sensors (cameras), restrictions due to traffic, fix points for image reference, this requires industry knowledge within reality capture. When operating in Denmark, the drones are not allowed to pass or fly above traffic lanes without traffic restrictions. The imagery for both pylons of the bridge was collected in one day.

Data Processing

Typically, a 70% overlap is achieved when capturing the picture to produce an incredibly detailed 3D model. The RGB images are then superimposed on top of the mesh. For a more comprehensive 3D mesh, imagery is gathered in the bridge splash zone (particularly vulnerable zone) with an 80% overlap. It requires bridge condition management experience (vulnerable zones, damage mechanisms, resolution needed for defect finding, etc.) to establish a detailed 3D model suitable for visual (virtual) inspection. The RCM model of both pylons was modelled in 2-4 days.

Data Analysis

The RCM model is imported into the COWI Virtual Inspection platform which is a web-based platform. The RGB and thermal images are imported into a picture panel. The picture panel displays the top 30 photos for the chosen location when you click on any area of the 3D model.

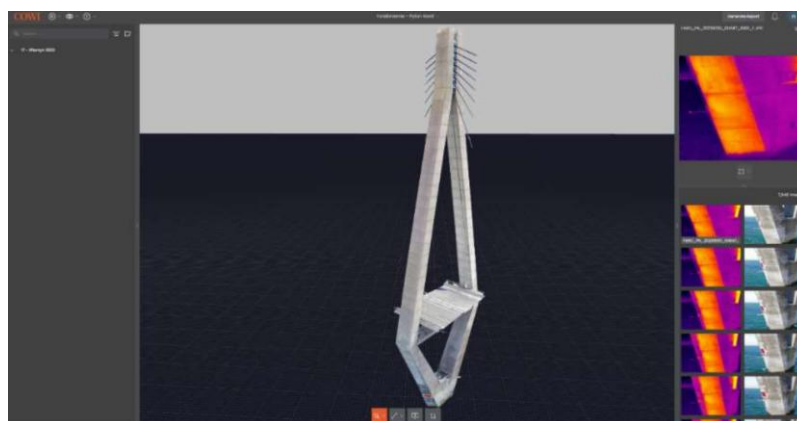


Figure E.4: The north pylon illustrated in COWI Virtual Inspection platform.

Annotations are used during virtual principal inspection to illustrate visible defects e.g., cracks, spalling, organic growth, graffiti, etc. The annotations are directly linked to the specific area of the model and are easy to flag and revisit.

CVI analyses the structure for corrosion, graffiti, and cracks using AI algorithms. The defects are annotated with a confidence interval and the inspection specialist is then able to sort the annotations and remove the non-critical defects. Only critical defects or defects to keep under observation are annotated and reported.



Figure 5.5: Example of AI annotation of cracks.

The AI algorithm is quickly developing for more accurate structural defect recognition as well as a wider range of defects, such as spalling, coating defects, honeycombing, etc. It is trained using pictures of existing structures that are utilised in CVI. The AI models are in general trained so that false positives are accepted (they are sorted out later during the manual visual inspection), but a false negative of a given size and especially in vulnerable regions (e.g., shear cracks in bridge half joints) is not accepted. In addition, it is important to use AI models that are trained for similar defect types.

In addition to RGB photos, thermal imagery can be used to identify areas that may not be visible on RGB photos, such as delamination, specific cracks and joints, concrete repair, and water ingress, where there is a temperature difference of only 0.1 to 0.2 degrees Celsius from the surrounding structure. The DJI Thermal Analysis Tool is used to scale the temperature interval of thermal photographs as seen in Figure E.6.

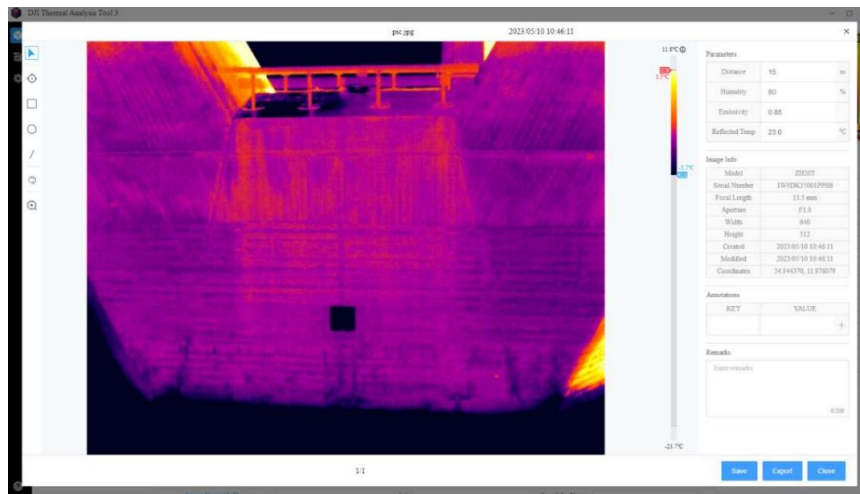


Figure E.6: Analysis of thermal images.

Data Representation

The web-based CVI platform is accessible to the asset managers. At project handover the manager is provided with a 3D Reality Capture Model with annotated defects, all RGB and thermal images. A PDF report is also generated in CVI as shown in Figure E.7. The report includes a written summary and an auto-generated description of findings based on annotations with additional photos of the defects.

The RCM can also be used to schedule upcoming repair projects, annotate daily operating tasks for operation staff, and other things. It offers a productive way to communicate with different owners, contractors, consultants, and stakeholders without having to physically be at the bridge site or worry about traffic limitations.

COWI Inspection Report

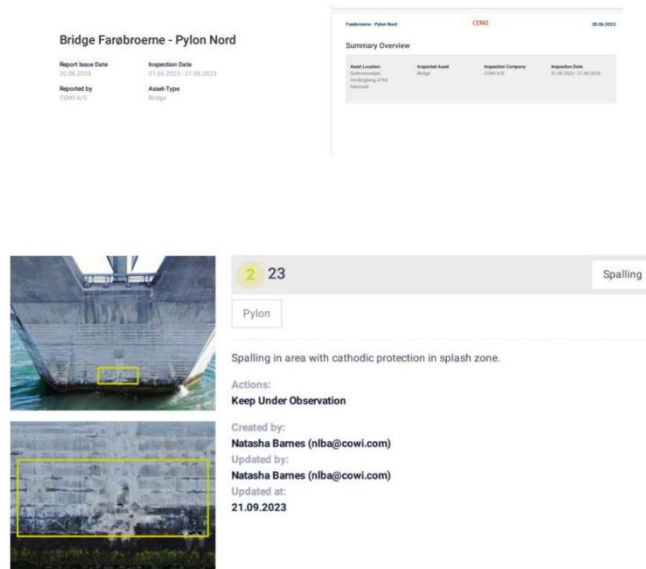


Figure E.7: Report with example of auto-generated description of findings.

Benefits

The costs associate with lifts, boats, climbing, and rappelling equipment for the bridge inspections were eliminated by the technology. The use of drones to inspect hard to reach areas also resulted in safety benefits, with no requirement for dangerous manual inspection of the bridge pylons.

Data collection benefits included the ability to collect data from the entire structure (100 % coverage of bridge surfaces) which contributed to a more comprehensive assessment of the bridge condition.

Drone inspection data analysis provided improved objectivity and the capacity to monitor the progression of defects over time. This made it possible to prepare and handle problems more effectively in early stages, ultimately reducing correction costs.

The representation of data was improved through the association of a 3D model with drone recordings, opening numerous future possibilities. Greater documentation for assessments was achieved, reducing reliance on a few photos and hand sketches.

Data representation was drastically improved with the created 3D model from the drone recordings data

RCM models can be analysed and compared over time to previous models to identify new defects and defect development to ensure that repairs are made at the best time. This leads to objective resource allocation and improved bridge maintenance decision-making efforts.

The use of drones for inspection also reduced the interference with traffic on the bridge, although in Denmark drones cannot fly above live traffic without any traffic restrictions.

Potential risks, barriers and implementation challenges

Multiple challenges arose during the implementation of the COWI Virtual Inspection Platform on the Faroe bridges in Denmark. Table E.4 highlights a number of these challenges faced and solutions to the challenges.

Table E.4: Barriers, risks and challenges faced by DRD in the implementation of COWI Virtual Inspection Platform.

Potential Challenge	Description	Solution
Data Collection	Challenges relating to the data collection included limitations on drone flight locations and additional costs associated with accessing difficult to reach places.	DRD collaborated with consultants to get an understanding of any limitations and to obtain necessary permits from the road authority.
Data analysis	One of the challenges in data analysis was the inability of AI to accurately annotate flaws.	This issue required an expert's manual evaluation to be resolved.
Limitations	DRD's current utilisation of the COWI Virtual Inspection Platform does not include data from beneath the water surface.	DRD believes that COWI has the capability to provide this in the future.
Data Visualisation	The high expense of creating a 3D model prevented DRD from having one of its own, which made data management more difficult.	Data integration into the existing architecture was not pursued to avoid associated costs.
Data Migration and Testing	There was no data migration from the old systems to the new one.	Through testing and validation against predetermined acceptance criteria, data accuracy, integrity, and system performance were guaranteed.

Cost

The initial implementation of the drone-based method made the condition survey approximately 50% more expensive due to the substantial cost of developing the 3D model. However, over time, the technology is expected to result in savings through faster defect detection and assessment, targeted future condition surveys based on objective data, and reduced expenses for access restrictions, lifts, and boats.

Concluding remarks

Overall, the implementation of the COWI Virtual Inspection Platform displayed promising in improvements in efficiency, data collection, analysis, and decision-making in bridge inspections for the DRD.

LANTERNN BY VALERANN USED IN LIMA, PERU

Case study description

This case study documents the use of the Lanternn by Valerann™ system in Lima, Peru, by the Lima Expresa road operator. Lima Expresa, owned by Vinci Highways, oversee the operations, maintenance and tolling of two key sections of highways in Lima, where the Lanternn by Valerann™ system has been implemented to assist control room operators with identifying and responding to incidents.

The two road sections operated by Lima Expresa are described below:

- Section 1, known as Vía de Evitamiento, is a 16 km long highway which forms part of the larger Panamericana Highway, as it passes through Peru, and serves as a bypass for the city of Lima. This section of the highway is in an Urban region and is characterised by a varied mix of traffic, which includes pedestrians, bicycles, and scooters alongside cars, buses and trucks.
- Section 2, known as the Línea Amarilla expressway, is a 9 km long route which is classified as an expressway due to the traffic flow and the restrictions on certain types of vehicles. This section of the highway leads to the Callao airport and port, next to Lima, and has high traffic volume as a result.

Figure E.8 provides an overview of the road network operated by Lima Expresa in Peru.



Figure E.8: View of the Lima Expresa road network map (Vimeo ibtta, 2024).

The use of Lanternn by Valerann™ was initially inspired following a pro-innovation competition held by the Peruvian government, which stemmed interest in the implementation of AI for incident detection and road operations. Lima Expresa won this competition with their proposed adoption of the Lanternn system on sections 1 and 2 on the Lima highway and the implementation of the system was part-funded by the Peruvian government under this initiative.

The system was introduced on a phased basis from early 2023. Initial setup, integration of data feeds and calibration of data fusion / AI algorithms was carried out between March-July 2023 and after this date, the system was introduced into the control room to assist with live operations.

Technology description

Lanternn by Valerann™ is a software platform which incorporates data fusion and AI algorithms for incident detection on roads. The system allows multiple data sources, both real-time and historical, to be integrated and fused. The system utilises the various data sources to generate alerts of potential incidents or hazards on the network. It provides road traffic operators with the necessary tools and insights to gain clarity of their roads' traffic situation in real-time and facilitates data-driven decision making. The system can utilise various available data sources including data recorded from fixed ITS equipment (e.g. CCTV cameras, radar etc.), floating vehicle data, Waze, weather data, etc. Figure E.9 shows screenshot of one instance of the graphical user interface for the Lanternn software system. The interface includes a map-based visualisation of the road network which shows the locations of incidents and interactive details about the data sources which have contributed to identification of the incident, along with any nearby cameras or ITS equipment. Information about individual incidents, relevant CCTV recordings (if available) or traffic speed information in the vicinity is also visualised on the interface.

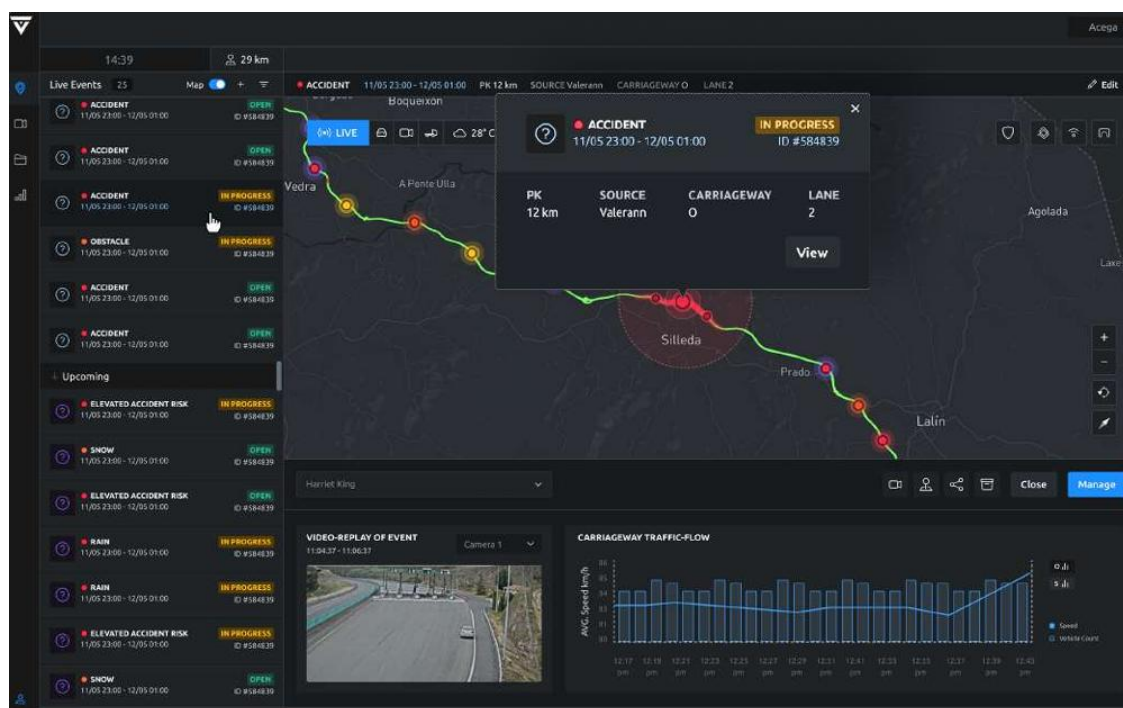


Figure E.9: Lanternn by Valerann™ graphical user interface (Vimeo ibtta, 2024).

Data sets (inputs / outputs)

The Lanternn system is based on a data fusion technology, coupled with AI, which works by integrating various available existing data sources such as Waze, HERE, CCTV Cameras and multiple other available data sources. Figure E.10 provides an overview of the different data sources which are used as inputs to the Lanternn system as part of the Lima Expressa's road operation.

AI-driven computer vision has been applied to the existing CCTV cameras, by taking direct feeds and using ML algorithms which have been trained to identify different types of events such as stopped vehicles, debris, pedestrians / animals on the road etc. The alerts coming from cameras serve as one data source which can be fused with all other available data sources to inform operators of live incidents, or high-risk areas, on the road network. Over time, the system continuously learns from user input and adjusts the relevance of the types of incidents which are considered to be of most interest to the operators. The system also allows false detections to be flagged as part of ongoing training of the underlying ML and data-fusion algorithms.

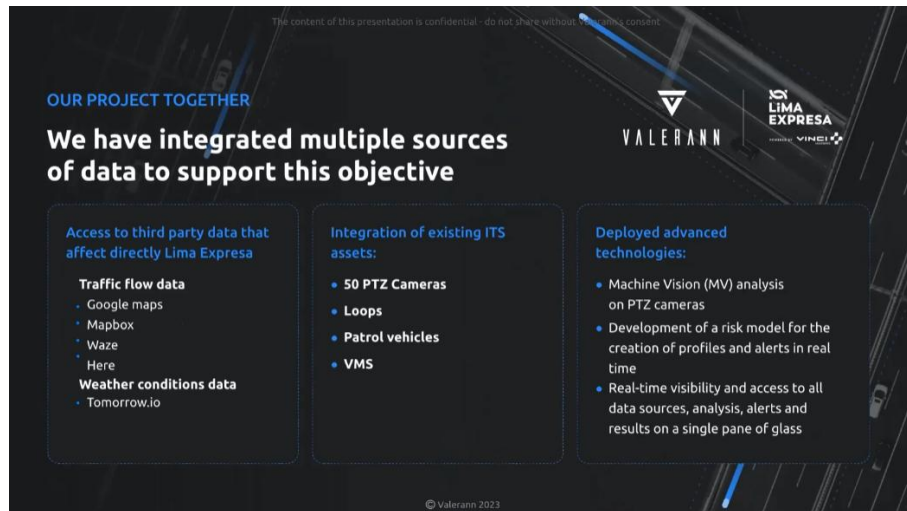


Figure E.10: Overview of data sources used as inputs to the data-fusion engine

Benefits

Lima Expressa achieved several benefits with the implementation of the Lanternn software for incident management.

Table E.5: Description of benefits achieved by Lima Expresa in the implementation of Valerann technology.

Benefit	Description
Incident Detection Times	The key performance indicator (KPI) which was set out by Lima Expresa was to identify 95% of incidents within 5 minutes. This target has been achieved and they are now detecting 96-97% of incidents within the 5-minute timeframe.
Response Times	There has been a 12% improvement in response time to incidents as a result in the improved incident detection time.
'Accidentability Rate'	The 'accidentability' rate is calculated as: [the number of accidents which led to deaths or injuries]*1,000,000/traffic level. This 'accidentability' rate has decreased from 2.63 in May 2023 to 2.22 in May 2024.
Transit Time	There has also been an observed reduction in transit time on section 2 of the Lima Expresa highway from 11 minutes to 9.9 minutes.
Reputational Benefits	Reputational benefits for the Lima Expresa road operator have also been noted, through their adoption of innovative technologies for improving road safety.
Operational Efficiency	Improvements in operational efficiency by reducing the workload for motorway operators.
Blackspot Identification	Incident blackspots and high-risk areas on the network can be readily identified.

These benefits represent a mixture of operational benefits to the road operator, in terms of road safety, and achieving their own incident detection targets, and also wider societal benefits in terms of reductions in death or injuries arising from road traffic collisions and improved journey times for road users. It should be noted that some of the observed benefits may not exclusively be attributed to the use of Lanternn, but may also include other factors. The key benefits achieved to-date are summarised in Table E.5.

Potential risk, barriers and implementation challenges

Although this technology achieved numerous benefits, there were a number of challenges faced during the implementation. It is noted that these challenges were generally quite minor and have been resolved over time with the approaches discussed below:

- **Calibration:** The initial calibration process for the system was distinctly different for the two road sections (S1 & S2), given their vastly different traffic characteristics.
- **Non-actionable alerts:** Detection of incidents which were not of interest was the primary challenge associated with the technology. This was an issue particularly for Section 1 of the highway where they experienced a lot of 'noise' due to the varied nature of road users between pedestrians, cyclists and vehicles. Some functionality had to be switched off for this section such as pedestrian detection to reduce the level of alerts received by operators.

Certain lanes on the road also had to be removed from the detection zone for the same reason. However, this was not a problem on S2, where the traffic was much more akin to a traditional 'freeway'.

- **Resistance to change:** Initially, due to change in workers' operations, control room operators were reluctant to utilise the new system. Each operator had to be trained in individually, one by one, and continuous training and upskilling was required as there had been a noticeable drop in operator engagement with the system. This continuous training helped improve the efficiency of the system and productivity of the operators.
- **Early-stage system limitations:** At the outset, there were some delays in the provision of access to dashboards and summary data which was a challenge at the beginning for operators.
- **Computational power / lagging response:** Due to the vast amounts of data that was being analysed by the system computer, some systems got overwhelmed when different data sources were leveraged simultaneously. This could result in the system freezing/crashing and causing difficulties with live operations.
- **IT integration expertise:** It is noted that input from the Lima Expressa IT department was essential for smooth integration of the data feeds into the Lanternn system, and also in terms of introduction of Lanternn into the control room. Without this input, there would likely have been a number of additional technical integration challenges.
- **Cyber security:** Cyber security represents a potential risk of this system, given the large quantities of data which are being ingested, the risk associated with hacking is increased. Relevant firewalls and IT security measures have been put in place to mitigate/minimise this risk.
- **Dependence on the system:** It was noted that control operations have become increasingly dependent on the system over time. Although this demonstrates the benefits and positive attributes of the system, it also means that the increased dependence of operators on Lanternn means that if it was to crash, or data was deleted/lost unexpectedly that it might cause problems for meeting their relevant Key Performance Indicators or Service Level Agreements, which would not be possible without the system.

Cost

The total costs of the ongoing implementation are not readily available, however, it is noted that the project was part-funded by the Peruvian Government. It was noted that there is typically an upfront cost for initial implementation, followed by ongoing maintenance & support fees for the period of operations. Although specific costs were not available for inclusion in this report, it is noted that the costs of using Lanternn by Valerann™ are likely to be a small fraction of the costs which would be required to install additional ITS equipment which could give the same level of coverage for incident detection through traditional technologies.

Legislation

It is noted that at the time of writing, there are no specific AI-related legal requirements which must be followed. However, local data security / privacy laws were particularly relevant due to the use and collection of potentially sensitive data.

Concluding remarks

Through the implementation of Lanternn by Valerann, Lima Expresa achieved numerous benefits and reached objectives which were set out at the beginning of the project. The main KPI of the project was met and multiple other benefits were accomplished. The transition from previous incident management systems took time and required the appropriate training for each operator to be able to utilise the system effectively. Technical challenges were all reasonably minor and were overcome without much difficulty, and people-related challenges were addressed through appropriate training, upskilling and educational awareness around the benefits associated with using the system.

ACUSENSUS USED IN NEW SOUTH WALES, AUSTRALIA

Case study description

This case study describes the experience of Transport for New South Wales (TfNSW) in the enforcement of mobile phone use and seatbelt offences using roadside cameras coupled with AI technology to identify infringements and facilitate issuing of fines to offending drivers. Mobile phone use is a leading source of driver distraction and naturalistic driving studies have shown a range of crash risks associated with hand-held mobile phone use (Wall et al., 2019). One study found that mobile phone use during or shortly before a casualty crash was associated with a fourfold increased likelihood of crashing (McEvoy et al., 2005). Another significant factor in road fatalities or serious injuries is incorrect seatbelt use. In NSW, on average, each year around 29 drivers and passengers are killed and around 79 are seriously injured in crashes when not wearing available seatbelts (NSW crash data 2017 - 2021). Not wearing a seatbelt was a factor in around 14% of fatalities between 2017 and 2021, and 19% of fatalities in 2021.

In an attempt to reduce illegal mobile phone use and incorrect seatbelt use, TfNSW have implemented an extensive program for automatically monitoring offences, and fining offending drivers. Initially in April 2018 a Registration of Interest process was announced to identify potential technology for a vision-based system that would automatically detect mobile phone offences on NSW roads. This led to an initial pilot, between January-June 2019, followed by a wider roll-out of the technology as part of the Mobile Phone Detection Camera (MPDC) Program which commenced in December 2019. This was later followed by the addition of automated enforcement of seatbelt-related offences, which commenced in 2024. Legislative changes came into effect in NSW from July 2018 which enabled camera-based technology to be used for enforcement mobile phone offences. Prior to TfNSW introducing this program, enforcement of mobile phone and seatbelt offences by drivers was primarily a function of the police, however the AI-based technology has allowed TfNSW to play an integral role in enforcement of safe driving on its network.



Figure E.11: Mobile camera for enforcement of mobile phone and seatbelt offences (Acusensus, 2024)

Table E.6 provides a general overview of the details of the initial pilot which was carried out in 2019, with

Table E.7 providing details on the wider roll-out of mobile phone detection as part of the MPDC Program. As part of the MPDC Program, TfNSW have enforcement cameras installed at multiple

locations on their road network, including fixed locations and mobile cameras which are moved around. They aim to check 135 million vehicles per year as part of their enforcement program.

Table E.6: Overview of TfNSW mobile phone detection pilot (January-June 2019).

Mobile phone detection (pilot)	Duration	No. of Locations
Initial test period (October 2018)	4 weeks	1
Phase 1	13 weeks	2 fixed
Phase 2	6 weeks	6*

Table E.7: Overview of TfNSW Mobile Phone & Seatbelt Detection Program.

Mobile phone detection camera program	Date(s)	No. of Locations
Warning letter period (3 months) for mobile phone	December 2019-February 2020	Multiple
Mobile phone enforcement	March 2020 - Present	
Seatbelt enforcement	July 2024 - Present	

Technology description

The technology, developed by Acusensus, employs AI powered cameras that can automatically detect drivers using mobile phones and not wearing seatbelts as seen in Figure E.12. These cameras utilise computer vision algorithms and real time processing for immediate detection and response to violations. Deep learning models have been used to improve the accuracy of the detection, these models are trained on large datasets to recognise patterns of behaviours associated with traffic violations.

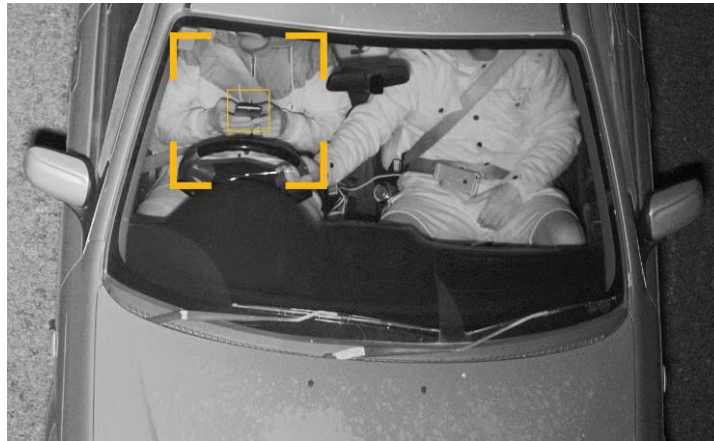


Figure E.12: Computer vision identification of driver mobile phone usage.

Once the AI-powered system automatically reviews the image and detects a potential traffic violation, it then flags the image for further review. All images that do not clearly show a traffic offence are permanently deleted. The flagged images are cropped to only show the space around the driver, removing the number plate and area around the car. The cropped images are then reviewed by a human operator to verify the offence. If the images do not show any offence they are, again, permanently deleted. Following human review, the images that contain potential traffic violations are encrypted and securely sent to a second human reviewer at TfNSW, where the images are pixelated outside of the space around the driver to maintain anonymity and privacy. If this human operator also identifies a traffic violation in the same image, then the image is again encrypted and sent for final review by trained officers at Revenue NSW and fine notices are then issued where an offence has been identified.

Data sets (inputs / outputs)

The AI algorithms require a few photographs of the vehicle to allow mobile phone or seatbelt offences to be detected, along with the car registration details which are required to issue a fine, where an offence has been confirmed.

The cameras capture 3 images of each passing vehicle, as described below:

- General photograph of vehicle, and number plate
- A shallow angle view of the vehicle's cabin
- A steep angle view of the vehicle's cabin

Benefits

The mobile phone detection camera program achieved several benefits which has led to safer roads and a shift in driver behaviour. The benefits associated with the mobile phone detection enforcement have been quantified through changes in the rate of infringements. Lovesy et al. (2023) reported the reduction in the rate of mobile phone infringements for the first 3 years since mobile phone enforcement commenced in March 2020, and the findings are reproduced in Table E.8, Seatbelt enforcement commenced in July 2024, and at the results in the first few months of implementation are included in Table E.9.

Table E.8: Number of vehicle checks, fines issued and infringement rates for camera-detected mobile phone offences in NSW (after Lovesey et al., 2023).

Year	Period	Vehicle Checks	Fines Issued	Infringement Rate (%)	1 in X Vehicle Checks
1	1 Mar 2020-28 Feb 2021	76,919,156	169,311	0.22	454
2	1 Mar 2021-28 Feb 2022	83,536,289	159,011	0.19	525
3	1 Mar 2022-28 Feb 2023	121,937,861	203,978	0.17	597
4	1 Mar 2023-29 Feb 2024	144,053,297	195,213	0.14	734

It can be seen from Table E.8, that the rate camera-detected mobile phone offences has reduced each year since the program began. Given the significant quantity of vehicles being checked, this represents a major reduction in the level of mobile phone use by drivers. Similarly, as reported in Table E.9, the rate of seatbelt infringements has significantly dropped since enforcement commenced.

Table E.9: Number of vehicle checks, fines issued and infringement rates for camera-detected seatbelt offences in NSW (Revenue NSW, 2024).

Month	Period	Vehicle Checks	Fines Issued	Infringement Rate (%)	1 in X Vehicle Checks
1	July 2024	12,169,224	16,560	0.14	734
2	August 2024	11,251,265	11,049	0.10	1018
3	September 2024	11,043,027	9,039	0.08	1221
4	October 2024	11,913,832	9,843	0.08	1210

It may be difficult to directly infer quantitative changes in collisions or road safety metrics due to these reductions in mobile phone or seatbelt offences. However, as discussed above, studies have shown that there is a direct correlation with fatal or serious injury crashes and thus, reducing these offences leads to safer roads with less fatalities and serious injuries as a result of distracted driving.

Potential risk, barriers and implementation challenges

The key risks and challenges associated with the introduction of AI-based camera enforcement related to data privacy, security and accuracy. TfNSW and Acusensus designed a robust approach to ensure that images were deleted almost immediately for any vehicles where no offence was detected. For vehicles where offences were detected, the blurring of parts of the photograph which

could be used to identify images, along with the various levels of human intervention required before an offender was issued a fine, meant that risks associated with data privacy were mitigated. Although there were some learnings along the way, it was reported that privacy protections were working well. It was also reported that the general public perception of the program was extremely positive, and that community support was maintained throughout the program. Following research conducted on a representative sample of NSW population, 79% of drivers believed the mobile phone detection camera program was an important measure in making roads safer.

In order to facilitate mobile phone and seatbelt detection, a new area of responsibility for TfNSW, some additional roles were required in the areas of policy, adjudication and contract management. However, apart from general resource management no specific challenges were reported in relation to lack of expertise for such roles within TfNSW. It is noted that careful planning and effective communication and collaboration between different departments and teams was considered key to the successful implementation of the program.

Legislation did not represent any specific new challenge, as the primary requirements related to compliance with the Privacy and Personal Information Act (1998), which is well established in Australia. Although NSW has published an AI Assessment Framework to guide NSW Government agencies through the ethical development, deployment and use of AI technologies, at the time of writing, there was no AI-specific legislation, relevant to the enforcement of mobile phone or seatbelt offences carried out by TfNSW.

Cost

The overall contract cost for the MPDC Program, from 1st December 2019 – 30th November 2024, have been publicly reported at \$41,782,770.00 (Australian Dollars). It is noted that this does not consider any internal costs for TfNSW related to any new roles or internal resources associated with the delivery of the program.

Concluding remarks

Transport for NSW have delivered an extensive program for automated detection and enforcement of mobile phone use, and seatbelt offences, using AI-based technology provided by Acusensus. Results have demonstrated significant reductions in the rate of mobile phone offences. The program has been successfully delivered without any significant challenges, and will continue into the future.

iRASTE PROJECT, INDIA

9.1.26. Case study description

Project iRASTE (Intelligent solutions for RoAd Safety through Technology and Engineering) was launched to combat road fatalities and reduce the number of deaths on roads by 50% by the year 2025. India has the highest rate of road accidents and fatalities globally and the Indian government, as a result, has made efforts to combat this low level of road safety. The project was implemented in Nagpur City and in the State of Telangana.

Multiple organisations worked in partnership during this project including International Institute of Information Technology (IIIT), Central Road Research Institute (CRRI), Mobileye and Mahindri each providing different functions in the project. The primary technology which was implemented used an AI-based ADAS, within buses, to provide various collision warning alerts to drivers. A smaller number of buses were equipped with a driver monitoring system (DMS) to monitor driver behaviour.

The four key objectives of the iRASTE project were vehicle safety, mobility analysis, infrastructure safety and training, education and awareness, as described below:

- **Vehicle Safety:** The project leveraged AI-based ADAS to improve driver reaction time to any incidents or sudden changes on the road. The project also included the use of DMS on 10 buses in the Telangana region which helps monitor distracted driving. Driver risk scores were obtained for each bus driver based on the number of alerts they were receiving. To incentivise safer driving, each month the details of the best and worst drivers were sent to depot managers so that they could be rewarded or selected for educational improvement, accordingly.
- **Mobility Analysis:** Greyspots on the road network were identified by the ADAS system based on the number of alerts that were flagged at specific locations. This was followed by designing cost effective engineering improvements for possible implementation.
- **Infrastructure Safety:** The identification of blackspots on the road network using First Information Report data that is related to road crashes obtained by the Police.
- **Training, Education and Awareness:** A 4-part training program has been developed by the project team to inform, increase safety awareness and educate drivers for the implementation of the new technology.

Full details of the project implementation in Nagpur City and In the State of Telangana can be found in the iRASTE executive summary for Nagpur City (iRASTE - Nagpur, 2024) and the State of Telegana (iRASTE - Telangana). The key elements of the iRASTE project are summarised in Table E.10.

Table E.10: High-Level Overview of the iRASTE Case Studies.

	Nagpur City	State of Telangana
Start – End date	September 2021 – September 2023	April 2023 – March 2024
No. of Buses equipped with Advanced Driver Assistance System (ADAS)	150	200
No. of driver monitoring systems (DMS)	0	10
No. of people trained in ADAS	1337	500

9.1.27.**9.1.28.****9.1.29. Technology description**

Within the iRASTE project, various technologies and road safety intervention measures were tested in two cities in India. The primary technology which was implemented used an AI-based ADAS within buses to provide various collision warning alerts to drivers. The ADAS system uses in-vehicle cameras and computer vision to analyse the surrounding environment in real-time as the bus is moving, and alerts are generated when potentially hazardous scenarios arise (i.e. pedestrians on the road, nearby bicycles etc.).

The primary components of an ADAS device include a camera unit and a display unit. The camera unit, positioned to capture the road ahead, is equipped with a powerful processor that processes video data locally. Advanced AI algorithms are used to detect risks in real time, eliminating the need to send video data to the cloud for processing, which improves efficiency.

Once a potential risk is detected, the camera unit alerts the driver via the display unit, which is fixed at eye-level. This display unit provides both visual and audio alerts to capture the driver's attention. Additionally, alert information is sent to a cloud portal, where it is archived for detailed offline analysis. Figure E.13 shows some examples of the different safety alerts which drivers can receive.

When combined with incentives associated with the number of alerts generated within buses, these alerts were also successfully used as a basis to encourage drivers to adopt safer driving practices. Mobileye, a leading technology provider in this industry, supplied the technology for the ADAS systems. The information and alerts generated from the ADAS system were also retrospectively analysed to identify potential areas on the road network where road geometry and driver behaviour combine to increase the likelihood of road crashes. These 'greyspots' serve as a leading indicator of road risk and can enable city authorities to plan or implement more safety interventions. This real time data approach is more accurate than typical traditional one-time surveys or other manual data collection efforts and is suitable for a large-scale deployment.



Figure E.13: ADAS Safety Alerts delivered to drivers (iRASTE – Telangana, 2024).

Also included in this system that was developed in the iRASTE project was a driver monitoring system (DMS), as shown in Figure E.14. This system utilised computer vision from multiple sensors and cameras inside the vehicle to monitor the driver's behaviour. Facial recognition technology tracks the driver's facial expressions, eye movements and head positions which can help detect signs of drowsiness or distractions such as use of mobile phones or smoking. Eye-Tracking technology further enhances safety by monitoring the driver's gaze to ensure they remain focused on the road, identifying any distractions caused by smartphones, dashboards, or other diversions. The system's alerting mechanisms provide real-time warnings for unsafe behaviours such as lane departures, following too closely, or veering off the road. Additionally, the data logging feature records and stores driver behaviour data, enabling detailed analysis and feedback for continuous improvement.

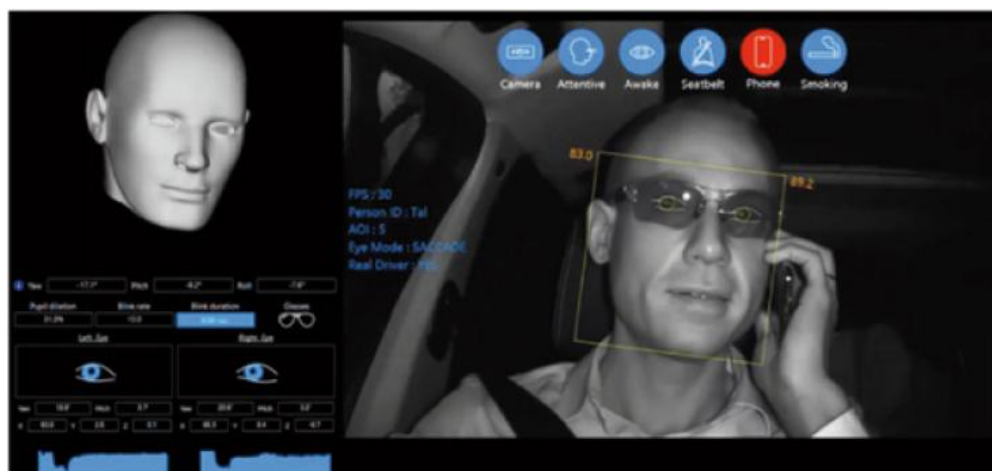


Figure E.14: Driver Monitoring System (DMS) which monitors driver behaviour inside vehicle (iRASTE – Telangana, 2024).

9.1.30. Data sets (inputs / outputs)

The ADAS and DMS require video footage which is used as the input to AI computer vision algorithms. GPS data is also collected to identify where the alerts appear, to help identify greyspots on the road network. The blackspot analysis was conducted using historical incident records.

The primary datasets are as follows: Inputs – Video feeds & historical incident logs; Outputs: Warning alerts.

9.1.31. Benefits

The iRASTE project resulted in a number of explicit benefits which were measured in each of the case study locations. It should also be noted that some of the observed benefits may not solely be as a result of the implemented technology, but are likely also influenced by the many other educational awareness campaigns along with training and safety workshops that were conducted as part of the project.

The benefits included societal benefits (identification of areas for infrastructure improvement) and some operational benefits to the road operator. There are multiple benefits which have arisen from iRASTE project, and are summarised Table E.11.

It is clear that there have been significant benefits achieved as a result of the iRASTE project, with major improvements in accident statistics in both cities, and an obvious improvement in driver behaviour within ADAS-equipped buses in Nagpur city. The identification of blackspots and greyspots have allowed areas of high-risk to be examined, and infrastructure upgrades have been designed to address the problems at a number of these locations already, with remediation works already completed or underway at many locations.

Separate to the infrastructure upgrades, community-based emergency first responder networks were installed at 8 blackspot locations in Nagpur City, equipped with first aid resources. These have enabled first responder volunteers to save 36 road crash victims (Aug 23- April 24) who were involved in crashes around these blackspots. In Telangana an Active Bleeding Control (ABC) training program initiative was launched, which included workshops at 7 locations. Over 600 first responders and volunteers were trained. These trained volunteers have already saved 4 lives in the past 5 months, showcasing the program's real impact.

Full details of all benefits associated with the iRASTE project can be found the iRASTE executive summary for Nagpur City (iRASTE - Nagpur, 2024) and the State of Telangana (iRASTE - Telangana, 2024)

Table E.11: Summary of the benefits achieved as part of Project iRASTE.

	Nagpur City	State of Telangana	Benefit type
Reduction in accidents	41%	40%	Mixture
Reduction in driver risk score (safer driving)	30%	Unknown	Operational
No. of Greyspots identified	16	60	Mixture
No. of Blackspots identified	38	65	Mixture
Improvement in reaction time	x2	x2	Operational
Improved signal adherence	24%	Unknown	Mixture

9.1.32. Potential risks, barriers and implementation challenges

There were a few minor challenges, risks and barriers in the implementation of the ADAS systems in the buses, but most of the challenges were overcome through general training and awareness campaigns. Table E.12 summarises the key challenges identified and how they were addressed during the project.

Table E.12: Summary of key challenges and risks encountered in Project iRASTE.

Challenge	Description	Solution
Resistance to change	At the early stages drivers worry from drivers about being monitored and potentially being reported to their managers. Driver scores fluctuated initially as they did not engage with the technology.	Education and awareness was provided through training workshops with drivers. Incentives were also provided to drivers who achieved the safest driving scores. These measures resulted in significant improvements.
Delays in providing infrastructure remediation	Lengthy processes for remediating road infrastructure at high-risk areas meant that it took a long time to implement upgrades.	A recommendation would be to engage in the civil engineering processes as early as possible to avoid delays in transitioning from planning and design, through to construction.
Data privacy	Collection of imagery from ADAS and DMS could pose data-privacy risks, however at the time when the iRASTE case studies commenced they were not subject to the new Digital Personal Data Protection Act which has recently come into effect.	Personal information was only recorded/used where necessary to facilitate driver-incentives for safe driving and driver education for poor driving performance.

9.1.33. Cost

Detailed whole-project costs were not easily quantified as there were many different initiatives and various associated costs. From the perspective of the camera costs, it was estimated that the cameras installed in each bus cost between somewhere in the range of ₹20k-₹50k (Indian Rupees), which is equivalent to \$250 - \$600 US dollars. The overall cost associated with cameras can be inferred based on the 500 buses in which cameras were installed across the two case studies, however other associated costs have not been reported.

9.1.34. Concluding remarks

This collaborative effort in two case-study regions in India have demonstrated how AI-based technologies can be leveraged to provide significant road safety benefits. The wide-reaching iRASTE project illustrates how a holistic approach, which includes training, awareness, public engagement and physical road infrastructure interventions, can maximise the potential impact of AI-based technologies.

TRL - MONITORING OF UNPAVED ROAD CONDITIONS USING SATELLITE IMAGERY AND AI**9.1.35. Case study description**

Transport Research Laboratory (TRL), in the UK, has created an efficient solution for assessing the condition of unpaved roads via high-resolution optical satellite imagery that is processed using artificial intelligence (AI) to categorise the condition of each length of unpaved road on a network, enabling roads to be prioritised for further inspection or treatment. The initial idea began in Nigeria in 2015 where TRL were asked to explore how satellites could contribute information to the road sector, with the condition of rural roads being selected for research.

TRL's solution was then further developed in a number of countries in Africa (Ghana, Uganda, Zambia, Tanzania, Kenya,) with a focus on unpaved roads. The team worked closely with road authorities and leveraged experience of developing the UK's industry survey standards. There are a wide range of unpaved roads in developing countries, each managed to meet local priorities and maintained to local budgets and resources. Recognising this, TRL has enabled its solution to be customised to local need and capacity, using the priorities and standards of the Local Road Authority (LRA) are foundational inputs to ensure a sustainable solution. Machine learning was then introduced to automate the process and increase efficiency and objectivity of the process. This was then followed up by a project won by TRL, funded by the European Space Agency (ESA), to assess the road condition in Madagascar and Malawi using satellite lower resolution imagery to reduce costs.

9.1.36. Technology description

The optical satellite images used by TRL are acquired from standard orbiting satellites, which can be tasked with providing specific imagery. The AI solutions used to process the images include customised and blended machine learning techniques. The condition data generated are used by local road engineers to prioritise the roads for further detailed inspection or treatment.

The machine learning model is calibrated to ensure assessments are in accordance with local materials, construction methods, and maintenance standards. Parameters for defect types and severity ratings are established through the collection of ground truth information on a representative sample of roads, using low-cost equipment that can be deployed in an LRA's vehicle to collect visual condition and roughness information. Once the model is calibrated, it is applied to the satellite imagery to produce a high-level assessment that applies the LRA's rating scale for roads. The variation in pixel intensity of the road surface is identified by the ML model and roads are categorised accordingly. Figure E.15 shows some typical unpaved road conditions that would be identified by the road classification algorithm and Table E.13 provides a detailed description of the process followed to implement the technology.

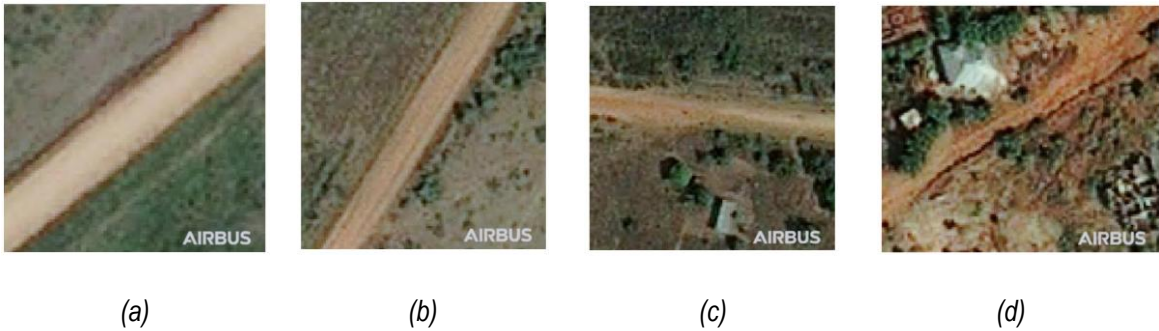


Figure E.15: Outputs of road classification from satellite imagery: (a) good, (b) fair, (c) poor, and (d) bad condition (Workman et al. 2023).

Table E.13: Summary of steps taken in the application of the TRL technology.

Step	Description
Define Requirements	Discussions are held with NRAs and local road authorities on what road condition assessments were required. The frequency and type of data was defined.
Acquire Imagery	The following satellite imagery suppliers were contacted; Pleiades, Satellogic Super, Vision 1 at 0.3m, 0.7m and 0.87m spatial resolutions respectively.
Clean Data	Tiles were then created through the QGIS model that was developed with the satellite imagery and the data was cleaned accordingly.
Calibration, Ground Truth	Ground truthing was conducted utilising a Dashcam mounted in a vehicle. The road roughness was measured using a smartphone app and the GPS tracks are colour coded to represent conditions.
Apply ML Model	Various classical machine learning models were used to determine the most accurate model. CNN models were also trialled for comparison.
Condition Analysis	The ML models' output was a condition analysis of the highlighted road network.

The results for Madagascar for the high-resolution imagery are 82.25% and 85.91% accuracy for basic and complex data sets respectively. These are higher than for Malawi, which can be explained by the higher proportion of gravel roads, as opposed to earth. The assessment of unpaved roads using the machine learning models in Malawi resulted in calculated accuracies ranging from 57% to 64%. Improvements were made to the ML model by using the top three classifier models only, which saw an increase in calculated accuracies to 82.5%.

A binary analysis was also done for roads in Madagascar to map cobblestone vs unpaved road surfaces. This resulted in accuracies of 95.4% - 99.1%, varying depending on the resolution of the satellite imagery. This would be useful for the LRA to identify areas where unpaved roads have been surfaced and records are not available.

9.1.37. Data sets (inputs / outputs)

The ML models require satellite imagery to be segmented into rectangular tiles. Three different satellite imagery resolutions were obtained for this project as seen in Table E.14, and the results were used to make a cost-effectiveness analysis of the different resolutions.

A plugin was developed for QGIS to allow the user to easily identify and create the tiles necessary for analysis from the satellite imagery, and import them directly into the ML model. This plugin is freely available via the QGIS software and is called ‘Earth Observation Pavement Analysis’.

Table E.14: Satellites and their associated costs and resolutions.

Imagery	Resolution (m)	Rate per km ² (€)
Pleades neo	0.3	26
Satellogic	0.7	10
Vision 1	0.87	7.5

9.1.38. Benefits

The project conducted by TRL achieved multiple benefits relating to road condition assessment and these can be seen below:

- Preventative maintenance processes can be put in place with more current and accurate information on the condition of roads.
- The improvement in road maintenance plans can lead to improved access to social amenities such as homes, schools and hospitals.
- There would be significant increases in the efficiency of maintenance efforts with a reduction in labour costs and time savings in undertaking of road network surveys.
- A cost effectiveness index was developed, based on analysis which included the resolution in metres, accuracy in percentage and cost per km of the various satellites. Using this index the Vision 1 satellite imagery was found to be the most cost-effective, as shown in Figure E.16

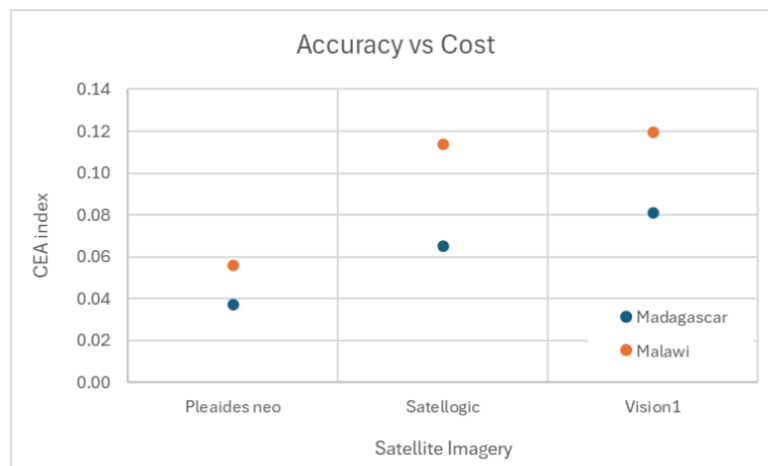


Figure E.16: Cost-effectiveness index for different satellite resolutions.

Potential risks, barriers and implementation challenges

The technology developed by TRL was generally well received by the countries that had implemented it however there were a few issues as noted below:

- **Procurement:** The procurement of satellite imagery can be challenging for LRAs in African countries who are not used to the process. Aside from the technical aspects, getting agreement to pay before receiving the imagery was not aligned with typical procurement approaches. A partner organisation, with experience in procurement of satellite imagery, was utilised during this process to help obtain the necessary imagery.
- **Computing Power:** Significant computing power is required to process the data. A GPU with large storage is used in the processing stage and this is not typically readily available in many LRAs. TRL were able to provide remote access to their computing facilities to facilitate the process.
- **Confidence in system:** Ensuring road authorities have trust in the system is a potential issue. However, scepticism was reduced and people became convinced once results for the system were demonstrated.
- **Software maintenance:** Continuous support is required for the system when there are software updates and for when people with expertise in the development of the tool leave the LRA.
- **Budget:** Budgetary issues were identified as all countries involved in the project were from Lower MICs and LICs. The imagery must be paid for in advance and often LRAs would be accustomed to paying for services after their use (as noted above). Continuity of funding from one year to the next was also noted as a concern for ensuring benefits of AI can be realised.

9.1.39. Cost

Total costs for the project were not published however, a cost-effectiveness analysis was conducted for the satellite imagery assessment process, projected to a country-wide level to demonstrate the potential for asset management. Lower resolution imagery was found to be less accurate, but roads authorities may be willing to accept a lower accuracy for a potential reduction of up to 75% in imagery costs. The cost-effectiveness analysis was produced to help them make that decision.

9.1.40. Concluding remarks

Through this project TRL have demonstrated and delivered more efficient monitoring of unpaved roads using satellite imagery. Significant time and cost reductions were achieved as a result of the implementation of the technology. The results of this project can help inform road authorities on where best to allocate resources for preventative road maintenance efforts.

VíaSegura - CLASSIFICATION OF ROADS IN SOUTH AMERICA BASED ON THEIR LEVEL OF SAFETY

9.1.41. Case study description

The Inter-American Development Bank (IDB) works on the development of technology that can benefit countries in Latin America and the Caribbean. In 2018, it began piloting AI technologies with the Department of Highways of the State of Paraná, Brazil, for crack detection of pavements using a computer vision tool. The AI model analysed 12,000km of surveyed road to detect cracks.

The model was then extended to road safety and utilised by the International Road Assessment Programme (iRAP) to provide safety ratings for the National Department of Transport Infrastructure. iRAP developed a star rating tool that assesses the safety condition of the road network. This road safety assessment helps inform investment strategies by identifying high risk road sections and implementing measures to mitigate safety risks.

The technology has been developed so that operators or private suppliers/contractors can drive specific roads of interest and use the platform to process the collected data. There are multiple accredited suppliers to gather road data. This accreditation is based on the accuracy associated with their feature detection. This data is fed into the model which allows iRAP to assign star ratings to sections of the road network.

The case study presented here highlights a combination of iRAP and other technology applications that have been implemented or tested through iRAP and the IDB across several countries in Latin America and the Caribbean. In particular, it focuses on key results from the State of Paraná, Brazil.

9.1.42. Technology description

VíaSegura is a tool developed by IDB that uses AI, specifically computer vision, to automatically detect essential road safety elements on highways. The model was trained and tested using 60,000 km of road data from Brazil, obtained by iRAP. The tool is open source and can be easily scaled to other cities and regions around the world. Within the region, it has been implemented in Honduras and Perú.

The model requires imagery with the specifications of iRAP's star rating system. The images must be taken every 20 metres along the entire path to be analysed correctly and accurately. The iRAP star rating tool provides an objective assessment of road safety by analyzing 45 road attributes that impact the risk for all road users, including pedestrians. VíaSegura can analyse 15 road safety elements of the 45 elements in the iRAP star rating systems, such as delineation, speed management, and road condition.

9.1.43. Data sets (inputs / outputs)

The tool uses video footage or road images as input and as a result, evaluates the condition of the following road features:

- Delineation, street lighting, carriageway, service road, road condition, skid resistance, upgrade cost, speed management, bicycle facility, quality of curve, vehicle parking, property access points, area type, land use, number of lanes.

9.1.44. Benefits

There are multiple benefits associated with the implementation of VíaSegura. The key benefits are summarised in Table E.15, along with a list with a detailed description.

Table E.15: Key benefits achieved through implementation of VíaSegura.

	Benefit
Reduction in time	56x
Reduction costs	39x
Road feature identification accuracies	67%-96%

- Automates the road safety analysis process and reduces the time required for road inspections. For every 10,000km of road, the time is reduced from 78 to less than 2 weeks. After the model was trained the system achieved a 56 times reduction in time taken for the road safety analysis of the network.
- Achieves a 39 times reduction in cost with the implementation of VíaSegura when compared to the manual costs of inspection.
- Analyzes 15 road safety features that work with the Road Assessment Program standards with accuracies ranging from 67% to 96%.
- Removes human subjectivity, resulting in more transparent and reliable diagnoses for authorities.
- Improvement in the repeatability of the survey process, as it is now faster and more cost-effective. This increased efficiency allows the process to be conducted more frequently, leading to a more accurate analysis of progressive deterioration.
- Road diagnoses have the potential to increase road safety and reduce accidents: a recent study by John Hopkins University analysed road modifications that have been implemented as a result of the iRAP methodologies, and concluded that iRAP tools have likely avoided 700,000 fatalities and serious injuries globally.
- New road designs can be analysed through the star rating tool, allowing road authorities to justify investments with a cost benefit analysis.
- Open-source python libraries and AI models that can be easily used and scaled (available [here](#)).

9.1.45. Potential risks, barriers and implementation challenges

There are a few barriers, risks and challenges associated with the technology.

- One of the primary challenges is that different data sources are suited to identifying different features, meaning the tool cannot yet detect all road features. Some features that haven't been fully trained into the model require human input, which is why a hybrid approach is being developed.

- The inconsistency in the frequency of certain features makes it challenging to train the model on all features. With limited data, there is a risk of bias in the dataset, which can lead to an inaccurate model.
- Accredited suppliers are required for the data collection process, as training individuals in the process can be difficult. iRAP collaborates with suppliers to verify the accuracy of source data and outputs, ensuring the appropriate level of classification accuracy is achieved.
- There may be concerns about diminishing the value of workers' expertise, leading to reluctance to adopt the technology. This was evident in low engagement and attendance at meetings with manual road maintenance workers, some of whom showed a fear of job displacement. However, in many cases, this tool can build upon their skills and expertise, allowing them to review and verify data more efficiently.
- There were some problems due to the limited computing capabilities in the region, such as the lack of cloud computing or GPUs to process the big data. To address this, local authorities uploaded the collected data to the IDB servers where data was processed.
- Some road authorities raised concerns regarding privacy and data security, leading to the requirement of Non-Disclosure Agreements (NDAs) to ensure that results are not made publicly available.

9.1.46. Cost

Currently, data collection costs are similar to manual processes due to upfront setup and training expenses. However, over time, these costs are expected to decrease to around 10% of manual collection costs. The system performs better with higher-quality cameras, which are more expensive, but it is compatible with most in-vehicle dash cameras. For more detailed studies requiring better GPS accuracy, improved image quality, 360-degree views, or LiDAR, higher-quality cameras may provide enhanced performance.

9.1.47. Concluding remarks

The combined efforts of the IDB and iRAP in Latin America and the Caribbean have delivered a high-quality, fast, scalable, low-cost solution for road condition assessments. The results of this collaboration can assist road authorities in identifying where resources should be allocated to improve road safety. With gradual implementation of technologies, it has the potential to provide significant benefits, including better classification of road infrastructure and improvements in the overall condition and safety of the road network over time.



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