FROM DATA TO DECISIONS: EXAMINING THE WESTERN CAPE'S USE OF AI TECHNOLOGIES TO ENHANCE ASSET CONDITION ASSESSMENT STRATEGIES IN ROAD INFRASTRUCTURE

M MAVANGWA[1], L MAFULAKO[1] and OA NNENE[2]

[1]School of Civil and Environmental Engineering, University of the Witwatersrand, Jan Smuts Ave, Braamfontein, Johannesburg 2017, South Africa;
Tel: 011 717 1000; Email: 2856889@students.wits.ac.za; lerato.molefe@wits.ac.za
[2]Department of Civil Engineering, Centre for Transport Studies, University of Cape Town, Rondebosch, Cape Town 7700, Western Cape, South Africa;
Tel: 021 650 4590; Email: obiora.nnene@uct.ac.za

ABSTRACT

In response to growing infrastructure demands and the need for safer, more efficient road networks, effective asset management is increasingly critical. This paper examines the current and potential use of Artificial Intelligence (AI) technologies in enhancing asset condition assessment strategies in the Western Cape province of South Africa. The study investigates how AI tools, such as predictive analytics, IoT sensors, and machine learning, could support real-time monitoring, performance evaluation, and predictive maintenance. The paper pursues three core objectives. Firstly, it compares traditional asset management and maintenance approaches with AI-based methods to assess their relative efficiencies and operational benefits. Secondly, it evaluates the status of AI adoption in the Western Cape using the Diffusion of Innovation (DOI) framework. Thirdly, it identifies the barriers and opportunities influencing AI implementation within the province's road infrastructure sector. Findings indicate that while there is growing policy interest in AI technologies, practical implementation remains limited. In contrast, national authorities like large state-owned entity under the authority of the Ministry of Transport. have made notable progress through AI-aligned systems, providing a precedent for provincial application. The study concludes that AI integration could significantly enhance road asset management by improving decision-making, resource optimization, and infrastructure resilience. Strategic recommendations include developing an AI integration policy, launching pilot projects, building technical capacity, and strengthening public-private partnerships. These insights offer valuable guidance for other regions facing similar infrastructure management challenges.

Keywords: Road Infrastructure Asset Management, Artificial Intelligence Applications, Predictive Maintenance, Digital Transformation in Asset Management, Machine Learning Models.

1. INTRODUCTION

1.1 Research Background and Context

According to Ben (2019), the road infrastructure is crucial for socio-economic development, providing essential connectivity for people, goods, and services. However, the road assets including pavement, bridges, culverts etc. are prone to deterioration due to climatic conditions, increasing traffic loads, and other environmental factors (Shao, et al.,

2017; Alamgir, et al., 2017). To ensure their safety, operational efficiency, and longevity, regular asset condition monitoring and effective management are essential (Radopoulou & Brilakis, 2016; Best, 2024). The International Organization for Standardization (2014) defines asset management as a systematic oversight of assets to derive or maximize value while managing associated risks, opportunities, and costs. In the context of road infrastructure management, this involves minimizing life-cycle costs through structured processes covering asset operation, maintenance, and upgrades (The Infrastructure Manager, 2018; Gericke et al., 2014). Effective asset management enables government stakeholders to identify assets requiring urgent intervention, optimize investment decisions, and maintain infrastructure performance at required service levels (Gavrikova, et al., 2020). Consequently, comprehensive and timely asset condition assessment and data collection are crucial to ensure that the required level of service is delivered economically.

Despite these advantages, traditional asset management practices are increasingly inadequate for addressing the complexities of modern urban and rural environments (Chang, et al., 2023). These practices typically rely on extensive manual visual inspections to assess road assets condition to determine its state and required maintenance (Bhardwaj & Goswami, 2019). In South Africa, road pavements are assessed using visual inspections guided by the TMH 22 manual, supplemented by instrument-based surveys, while road structures such as bridges and culverts are evaluated using the TMH 19 guidelines (Committee of State Road Authorities, 1995). While these traditional methods have been effective in certain contexts, they are labour-intensive, costly, and prone to human error (Chang, et al., 2023). Their reliance on periodic, manual assessments limits the ability to obtain real-time asset condition information and implement proactive, predictive maintenance strategies (Best, 2024).

Emerging Artificial Intelligence (AI) technologies offer promising alternatives to overcome these limitations (Rashid & Kausik, 2024). Tools such as Machine Learning (ML) algorithms, Internet of Things (IoT) sensors, and advanced analytics platforms enable automated, accurate, and continuous asset condition monitoring (Murtaza, et al., 2024). ML can analyse extensive datasets to identify deterioration trends, predict failures, and optimize maintenance scheduling using both supervised and unsupervised machine models (Arena, et al., 2024). Similarly, IoT sensors can facilitate real-time performance monitoring and early detection of asset distress (Syafrudin, et al., 2018). Therefore, integrating these innovations could significantly reduce dependence on manual labour, improve decision-making, and enhance the cost-efficiency and resilience of road asset management systems (Tamagusko, et al., 2024).

This paper seeks to examine the use of AI technologies in the Western Cape to enhance asset condition assessment strategies. It applies the Diffusion of Innovation (DOI) framework to evaluate the extent to AI adoption and to identify the factors influencing its uptake within the region's road infrastructure asset management practices.

1.2 Research Problem Statement

Despite the global advancements in AI technologies and their transformative potential in road infrastructure asset management, their use in the Western Cape primarily at provisional and district levels remains limited. Traditional asset management practices, reliant on manual inspections and periodic condition assessments, are proving increasingly inadequate for addressing the complexities of modern infrastructure needs, increase population and the rising demands for efficiency, cost-effectiveness, and sustainability. The key challenge lies in the gap between advancements in AI technologies,

their limited adoption and application in the Western Cape. There is a notable absence of pilot projects or widespread use of these technologies to enhance asset condition assessments, real-time monitoring, and predictive maintenance strategies particularly at provincial and district level.

1.3 Research Aim

This paper aims to examine the extent and current use of AI technologies in road infrastructure management within the Western Cape using the Diffusion of Innovation (DOI) framework. It addresses the need to understand their application, benefits, and barriers. By exploring this gap, the paper seeks to evaluate how AI technologies can improve asset condition assessments and inform more effective maintenance strategies.

1.4 Research Scope

The scope of this paper focuses on examining the use of AI technologies in road infrastructure asset management within the Western Cape. It explores how various AI tools are employed for real-time asset monitoring, continuous performance evaluation, and predictive maintenance. The paper further compares traditional asset management methods with AI-based approaches to evaluate their relative benefits. It assesses the extent of AI adoption in the region and identifies barriers influencing its implementation. Ultimately, the paper provides insights into the potential use of AI technologies to improve asset condition assessment, efficiency and effectiveness within road asset management practices in the Western Cape province.

2. OVERVIEW OF TRADITIONAL ROAD ASSET MANAGEMENT AND MAINTENANCE STRATEGIES

Traditional road asset management and maintenance strategies are positioned on preserving the functionality, safety, and longevity of road infrastructure through well-established, manual, and reactive practices (World Bank, 2018; UNECA, 2020). These strategies have been applied globally and are often tailored to the specific conditions of each region, such as traffic loads, climatic influences, and budgetary constraints (OECD, 2019). In traditional practices, road maintenance activities are categorized into routine, periodic, and emergency maintenance. Where routine maintenance involves regularly scheduled activities, such as cleaning drainage systems, filling potholes, and maintaining road markings (Roodt, 2016). Periodic maintenance entails more substantial efforts, like resurfacing or applying protective treatments, upgrading erosion protection around drainage structures etc. which are carried out at predetermined intervals to extend the lifespan of the asset (FHWA, 2022). Emergency maintenance addresses unexpected damage caused by natural disasters, accidents, or other unforeseen events (SAICE, 2022).

A common feature of traditional road asset management is the reliance on manual inspections and condition surveys to evaluate the conditional state of road infrastructure assets (Adey, 2018). These surveys, often conducted by trained personnel, involve visual inspections and basic measurement tools to identify defects, such as cracking, rutting, or drainage issues (UNECA, 2020; Department of Transport, 2018). The study Owuor and Sang (2022) indicated that, the maintenance strategy will usually involve analysing historical data and periodic condition assessments to schedule maintenance activities. Although useful, these traditional practices are limited by their inability to process real-time condition data and predict future road conditions with precision (OECD, 2019). Globally, traditional strategies are also influenced by regulatory frameworks and funding

mechanisms (Camane, 2013; Hagerman, 2012). Many countries rely on fuel taxes, road tolls, or government budgets to finance road maintenance (World Bank, 2018; SAICE, 2022). These funding models, are often insufficient to meet the growing demands for road infrastructure upkeep, leading to maintenance backlogs in many regions (Krygsman, 2024; DBSA, 2023). While traditional road asset management practices have supported infrastructure development for decades, they face challenges in addressing modern demands for sustainability, resilience, and efficiency (UNECA, 2020; OECD, 2019).

3. OVERVIEW OF ADVANCEMENTS IN AI TECHNOLOGY FOR ROAD ASSET MANAGEMENT

The International Transport Forum (ITF) (2021), refers AI as an umbrella term for a suite of transformative technologies, enables computer systems to replicate complex human decision-making in challenging environments. In the realm of road infrastructure asset management, AI has emerged as a game changer, revolutionizing traditional practices by enhancing the efficiency, precision, and responsiveness of maintenance processes (Chang, et al., 2023). As infrastructure networks face increasing strain from increase in traffic loading, aging assets, and unpredictable weather patterns, AI provides a lifeline, offering innovative tools to address these challenges head-on (ITF, 2021). The study by Rashid and Kausik (2024) underscores the unprecedented potential of AI in empowering road professionals to analyse vast datasets, automate intricate tasks, and devise more effective asset condition assessment strategies. By leveraging the power of AI, road asset management is no longer reactive but predictive and proactive, allowing authorities to anticipate issues before they arise and optimize interventions to extend the lifespan of infrastructure (Rashid & Kausik 2024; Plevris & Papazafeiropoulos, 2024). Beyond traditional practices, AI technologies open doors to intelligent, data-driven management practices (Gupta & Parmar, 2024). From machine learning models that predict pavement and structural deterioration, to IoT sensors that enable real-time asset condition monitoring, the possibilities are expansive (Tamagusko, et al., 2024). These advancements signal a paradigm shift, where infrastructure management evolves into a dynamic, responsive system capable of meeting future demands (Alahi, et al., 2024). Below is one of the groundbreaking AI technologies that provide the foundation for predictive, proactive, and intelligent road asset management strategies, setting them apart from traditional practices.

3.1 Machine Learning: Transforming Road Asset Management

Machine learning (ML) a subset of AI technologies, is revolutionizing traditional approaches in road asset management by enabling asset condition assessment predictive, efficient, and data-driven solutions (Soori, et al., 2023; Tamagusko, et al., 2024). With its ability to process vast amounts of data, recognize patterns, and generate informed predictions, ML is paving the way for more accurate and timely evaluation of asset conditions (Surur, et al., 2025). Unlike conventional/traditional manual inspection, which are not only time-consuming but also prone human vulnerability and subjectivity including error and oversight – ML can automate complex assessment tasks, providing real-time, data-driven insights that enhance the accuracy and efficiency of road condition evaluations (Cano-Ortiz, et al., 2022). Furthermore, when integrated with complementary technologies such as the Internet of Things (IoT) sensors embedded on road assets (e.g. the soffits of bridges or culverts), ML can significantly enhance the precision, responsiveness, and scalability of asset monitoring system including condition assessment strategies (Hoang, 2024). In the context of Western Cape, where authorities face mounting pressure to address maintenance backlogs, weather-related damages and service delivery concerns,

the adoption of such intelligent system offers a pathway towards more transparent, responsive, and sustainable asset management practices.

ML encompasses three primary methodologies: supervised learning, unsupervised learning, and reinforcement learning – each contributes uniquely to road infrastructure management and asset condition assessment. These methodologies are reviewed below and as shown in Figure 1.

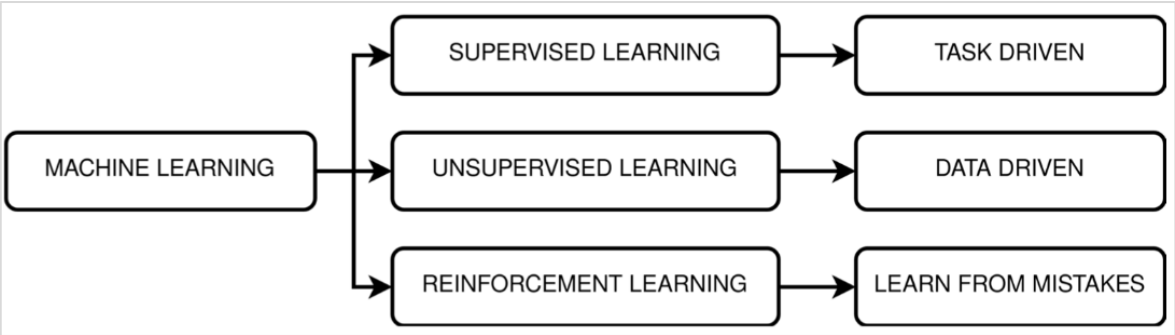

Figure 1: Machine learning methodologies adapted from Tamagusko et al. (2024)

3.1.1 Supervised Learning

The study of Alzubaidi, et al. (2021) described supervised learning (SL) as a method where algorithms are trained on labelled datasets, where the inputs are paired with known outputs. In the context of road asset management, supervised learning excels in tasks like pavement condition assessments. For example, linear regression is one type of SL algorithm which can analyse road images to detect cracks, potholes, or rutting, classifying defects with remarkable accuracy (Shtayat, et al., 2022). Conversely, structural monitoring can also benefit from SL, as models process sensor data from bridges and culverts to detect anomalies like excessive stress or deformation (Alzubaidi, et al., 2021). According to Fahad and Bektas (2025), a typical predictive maintenance model for estimating pavement service life using supervised learning can be represented by a linear regression equation:

$$Y = C + a_1 X_1 + a_1 X_1 \ldots a_n X_n \quad (1)$$

Where:

- Y = Predicted pavement condition index (PCI) or remaining service life (output value)
- C = Output variable values
- a_n = Regression coefficients
- X_n = Predictor/input variables (e.g., traffic volume, temperature, crack density, rut depth, historical maintenance records, sensor-based strain data etc.)

Therefore, this type of model can enable infrastructure asset managers to forecast pavement deterioration trends and optimize maintenance scheduling based on real-time and historical data inputs.

3.1.2 Unsupervised Learning

Unsupervised learning (UL), on the other hand, does not rely on labelled datasets but instead identifies patterns and clusters within unstructured data (Tamagusko, et al., 2024). This approach is particularly valuable for clustering road infrastructure assets based on their condition states or for detecting irregular patterns in sensor data (Naeem, et al.,

2023). For example, UL models can cluster pavement segments based on their deterioration levels, enabling maintenance strategies (Alnagbi, et al., 2024; Tamagusko, et al., 2024). Similarly, they can identify anomalies in drainage system sensor data, such as irregular water flow rates or sediment accumulation, which may indicate blockages or imminent structural failures (He, et al., 2023). A commonly used clustering technique is K-means clustering, which partitions data into *k* groups by minimizing the within-cluster variance (Ikotun, et al., 2023). According to Sharma (2025), K-means algorithm can be mathematically expressed as:

$$J = \sum_{i=1}^{k} \sum_{x} || \, x - \, u_i \, ||^2 \tag{2}$$

Where:

- k = number of condition clusters (e.g., Good, Fair, Poor)
- x = a vector of condition variables for a particular asset
- u_i = centroid (average value)
- $|| \, x - \, u_i \, ||^2$ = squared distance between a data point x and the centroid u_i

Therefore, this type of model can enable infrastructure managers to categorize any road assets based on multiple condition indicators, improving inspection prioritization, intervention planning, and lifecycle management.

3.1.3 Reinforcement Learning

Reinforcement learning (RL), the third major ML paradigm, is a decision-making approach where models learn optimal actions through interaction with their environment. RL applications in road asset management include dynamic maintenance scheduling and adaptive traffic management (Tamagusko, et al., 2024). For example, RL models can balance the trade-offs between maintenance costs, road conditions, and traffic disruptions, optimizing intervention schedules for maximum efficiency (Lai, et al., 2024). Similarly, in traffic management, RL systems can dynamically adjust routing to minimize wear and tear on heavily trafficked road segments, thereby extending their lifespan (Swapno, et al., 2024). According to Chen, et al. (2024), RL algorithm also known as Q-learning can be expressed as follows:

$$(s_t,a_t) \leftarrow (1-\alpha) \cdot Q(s_t,a_t) + \alpha \cdot (r_t+1 + \gamma \cdot max \; a(s_t+1,a_t)) \tag{3}$$

In road infrastructure condition asset management, the state (s_t) could represent current road or bridge condition ratings and traffic load, actions (a_t) might be maintenance decisions (e.g., no action, minor repairs, or full rehabilitation), and the reward (r_t) could quantify operational cost savings or condition improvement. Over time, the RL model learns a policy that selects actions maximizing long-term value, balancing budget constraints with asset performance objectives (Chen, et al., 2024).

Preceding the above, the integration of ML with IoT further amplifies its impact on road asset condition management. IoT sensors such as strain gauges, accelerometers and displacement sensors (also known as LVDTs) embedded on pavements and drainage systems (bridges and culverts) can continuously monitor parameters such as stress/strain, temperature, vibrations, deflection and cracks (Alahi, et al., 2023; Flah, 2020; Vaisala, 2024). These sensors create a network of interconnected devices, transmitting real-time data to centralized systems (Bhattacharya, et al., 2022). ML algorithms then process this data to detect anomalies, predict failures, and recommend maintenance actions. For example, if IoT sensors identify excessive strain in a bridge, an ML model can analyse the data to assess the structure's integrity and suggest immediate intervention (Alahi, et al.,

2023; Dikshit, et al., 2023; Flah, 2020; Barlow, et al., 2022; Heravi, et al., 2024). The synergy between IoT sensors and ML creates a robust system capable of automating large-scale road condition assessments with unmatched precision.

3.2 Limitations of AI Adoption

While AI adoption in road asset management presents notable benefits but is not without limitations. According to Ayeni (2025), key challenges include data quality issues, model overfitting, limited interpretability of complex models, and integration difficulties with existing systems. Additionally, biases in historical data, high computational demands, and regulatory concerns can hinder implementation (Xie, et al., 2025). These factors may affect the reliability, fairness, and operational feasibility of AI-based predictive models (Sinha & Lee, 2024). Therefore, addressing these limitations through improved data management, explainable AI techniques, and policy frameworks is essential.

4. COMPARISON OF TRADITIONAL PRACTICES WITH AI TECHNOLOGY FOR ROAD ASSET MANAGEMENT

The integration of AI into road asset management presents significant improvements over traditional methods, especially in areas such as data accuracy, predictive analytics, and real-time condition monitoring. Table 1 outlines the key characteristics, advantages, and limitations of conventional bridge condition assessment practices, focusing on aspects such as data analysis, detection, automation, prediction, inspection, and human factors. In contrast, Table 2 presents how these same aspects are addressed using AI-based tools and techniques. Finally, Table 3 provides a high-level comparison of traditional and AI-driven approaches, emphasizing the transformative potential of AI technologies in enhancing the efficiency, scalability, and responsiveness of infrastructure management.

Table 1: Traditional bridge condition assessment practices

Characteristic	Advantages	Disadvantages	References
Data Analysis	Utilizes established engineering judgment and historical records.	Often lacks real-time data integration and comprehensive analytics. May also not effectively handle large datasets.	Wang, et al. (2009)
Detection	Experienced inspectors can identify visible defects through visual inspections.	May miss early-stage or subsurface defects not visible to the naked eye. Relies heavily on subjective assessments.	Omar and Nehdi (2018)
Automation	Minimal reliance on complex technology, reducing initial costs.	Limited automation leads to time-consuming processes and increases the potential for human error and inconsistency.	Dorafshan (2018); Bridhenti, et al. (2024)
Prediction	Based on historical performance and expert intuition.	Lacks predictive modelling capabilities and cannot accurately forecast future deterioration or maintenance needs.	Omar and Nehdi (2018)
Inspection	Direct, hands-on evaluation allows for immediate observations.	Labour-intensive and potentially hazardous for inspectors.	Beshr, et al. (2025); Omar and Nehdi (2018)
Human Factors	Leverages human expertise and adaptability in complex situations.	Subject to variability in skill levels and potential for oversight. Fatigue and environmental conditions can affect performance.	Dorafshan (2018)

Table 2: Advantages and disadvantages of using AI tools in assessment of the technical condition of bridges

Characteristics	Advantages	Disadvantages
Data Analysis	Increased accuracy and speed of processing large amounts of data	Dependence on data quality, difficulty in interpreting results
Detection	Early detection of damage through the detection of anomalies and patterns	Need for a large amount of data for training
Automation	Automation of routine tasks, freeing up engineers' time	High implementation cost (hardware, software, training)
Prediction	Remaining resource forecasting and optimizing scheduling/budgeting	Need for qualified specialists for development, implementation, and support
Inspection	Monitoring in hard-to-reach places using drones and robots	Cybersecurity issues and vulnerability to cyberattacks
Human Factors	Reducing the impact of human error	Need for highly qualified personnel

Source: Trach, et al. (2025)

Table 3: High-level comparison of traditional practices with AI-based approaches

Aspect	Traditional Practices	AI-base Practices	Reference
Data Collection	Relies on periodic inspections and limited historical records. Assessments are often based on static snapshots of infrastructure condition.	Utilizes real-time data collected from IoT sensors, drones, and other monitoring systems, combined with historical data for trend analysis.	Rajta (2024)
Analysis and decision-making	Relies on subjective judgment and experience from expertise, leading to inconsistent evaluations and reactive maintenance strategies	Employs machine learning algorithms to analyse data, identify patterns, and predict future deterioration, enabling proactive maintenance planning.	(ITF, 2021)
Maintenance scheduling	Based on fixed intervals or visible deterioration, often resulting in over- or under-maintenance.	Predictive maintenance models forecast optimal intervention times, reducing unnecessary repairs and preventing failures.	Rajta (2024)
Resource allocation	Limited data integration leads to inefficient use of resources and higher costs.	AI systems optimize resource allocation by analysing comprehensive data sets, improving cost-effectiveness.	Rajta (2024)
Scalability	Manual processes are challenging to scale across large infrastructure networks.	AI-driven solutions are inherently scalable, allowing for efficient management of extensive road networks.	ITF (2021); Rajta (2024); Keleko, et al. (2022)
Accuracy and reliability	Prone to human error and subjective assessments, leading to potential safety risks.	AI technologies provide consistent, objective, and precise evaluations, enhancing safety and reliability.	Rajta (2024); Keleko, et al. (2022)

5. CASE STUDY DESCRIPTION: ASSET MANAGEMENT AND MAINTENANCE STRATEGIES IN THE WESTERN CAPE

The Western Cape is one of South Africa's most prominent provinces, located in the southwestern corner of the country. The Western Cape's road network spans over 33 000 kilometers, across six district municipalities. It comprises national roads like the N1, N2, and N7, managed by the large state-owned entity under the authority of the Ministry of Transport for interprovincial connectivity; provincial roads, maintained by the provincial government, linking towns and agricultural regions; and district municipal roads, overseen by local authorities for urban and residential access (SAICE, 2022). The Western Cape province was chosen for this case study because it is a coastal province that has distinct environmental challenges in terms of road infrastructure maintenance, such as

environmental factors including coastal erosion and flooding, and increase in road usage (traffic loading) due to semigration and heavy trucks. Figure 2 illustrates the locality of the Western Cape.

Figure 2: Western Cape locality and district municipalities (retrieved online)

The case study approach was considered suitable for this study because it enables an in-depth contextual analysis of asset management and maintenance strategies within a specific, bounded setting. This method was particularly appropriate for exploring the use of AI in road asset management within the province's unique operational, environmental, and institutional context. While a mixed-method approach (combining quantitative data analysis with qualitative insights from interviews or surveys) could have provided a broader perspective, it was not feasible for this study. Due to the timing of the paper's submission, ethics clearance the school ethics committee for conducting mixed research involving human participants had not yet been obtained. As a result, interviews and survey-based data collection from road asset management stakeholders could not be conducted within the required timeframe. Furthermore, approvals from research sites for interviews and data gathering were also pending at the time of submission. Consequently, the case study approach, relying on readily publicly available reports, asset management plans, academic literature, and documented practices in the Western Cape, was the most feasible and methodologically sound option for achieving the study's objectives within the given constraints. This approach not only aligned with the scope and timeframe of the research but also allowed for the exploration of AI adoption trends and infrastructure management strategies without the ethical limitations associated with direct stakeholder involvement.

The asset management practices in the province are largely governed by Road Asset Management Systems (RAMS), which aim to ensure that maintenance is carried out systematically (Department of Transport, 2018). The province adopts Pavement Management System (PMS) at provincial, district and national road network level to manage and maintain the condition of road surfaces. They also adopt Bridge Management System (BMS) for management of road structures (bridges and culverts). These systems follow a traditional road asset management and maintenance strategies which have historically emphasized reactive and preventive maintenance approaches (Department of Infrastructure, 2024). At provincial level, these strategies are outlined in the Western Cape Government's Road Asset Management Plan 2019/20 to 2028/29 Volume 1 and 2.

In recent years, there has been a shift towards more systematic and data-driven approaches to road asset management in the Western Cape. The provincial government have implementation of the Road Network Information System (RNIS) has enhanced the province's ability to collect, store, and analyse data on road conditions, facilitating more informed decision-making regarding maintenance and resource allocation within its road network including of district municipalities road network (Department of Infrastructure, 2024). They also use platform such as Structured Road Asset Management System (STRUMAN) to manage both PMS and BMS within the province. On the other hand, City

of Cape Town and the large state-owned entity under the authority of the Ministry of Transport also employs RAMS. However, they manage their PMS using specialized software platforms like dTIMS, which enable data-driven maintenance planning, performance prediction, and lifecycle cost analysis. Despite these advancements, several challenges continue to persist including reliance on inspectors to accurately collect, rate condition of asset and store collected data. Additionally, budget constraints, aging infrastructure and environmental stressors continue to impact the effectiveness of the current road asset management practices and maintenance strategies within the Western Cape, highlighting the need for innovative solutions to enhance infrastructure resilience.

6. FACTORS INFLUENCING AI ADOPTION

The adoption of AI in road asset management is influenced by several interrelated factors, including technological, organizational, economic, and regulatory considerations. Technological readiness, such as the availability of IoT sensors, and data integration systems, is crucial for implementing AI-driven solutions (Rane, et al., 2024). Additionally, the quality, volume, and accessibility of data significantly impact the success of AI models in condition assessment and predictive maintenance (Luan, et al., 2022). On the other hand, organizational factors include leadership support, staff expertise, and a willingness to adapt traditional practices to innovative, data-driven approaches (Rane, et al., 2024; Luan, et al., 2022). Furthermore, resistance to change and a lack of technical skills can hinder AI adoption (Alhosani & Alhashmi, 2024). The economic considerations also play a vital role, as high initial costs of AI implementation, including software, hardware, and training, can deter organizations with limited budgets (Rane, et al., 2024). However, long-term cost savings from improved efficiency and reduced maintenance costs can incentivize adoption. Lastly, regulatory and ethical frameworks influence the pace of adoption (Department of Infrastructure, 2024). Governments and regulatory bodies must establish clear guidelines for using AI in public infrastructure, addressing concerns around data privacy, accountability, and interoperability (Department of Infrastructure, 2024; Rane, et al., 2024). Together, these factors determine the feasibility and pace of integrating AI into road asset management systems, emphasizing the need for a balanced approach to address technological and human-centric challenges.

7. METHODS

7.1 Methodological Framework

The methodological framework serves as the foundation for this study, guiding the systematic exploration of the use of AI technologies in road asset management within the Western Cape. By employing a case study design, this paper aims to investigate the extent of current use, barriers, and adoption rates of AI technologies across the province.

7.1.1 Case Study Design

A case study is an empirical research method that allows for an in-depth exploration of contemporary phenomena within their real-world contexts, particularly when the boundaries between the phenomenon and its environment are not clearly defined (Yin, 2014). This study employs a case study approach to investigate the implementation of AI technologies for road asset management in the Western Cape. Specifically, it examines how AI integration impacts road asset management processes, explores the factors driving or hindering adoption, and assesses the rate of AI adoption within the provincial government's asset management framework.

Figure 3: Case study design flow chart (Own study)

The case study flow chart (Figure 3) outlines the systematic approach used to connect empirical data with research questions and conclusions. The five components of the case study design, as proposed by Yin (2014), include identifying research questions, study propositions, the unit of analysis, linking data to propositions, and interpreting findings.

The research questions guiding this study are as follows:

i. How does the use of AI technologies compare to traditional road asset management practices in the Western Cape?

ii. At what stage of the five-step adoption process and as indicated in Figure 4 is the provincial government, district municipalities and large state-owned entity under the authority of the Ministry of Transport regarding the use of AI technologies for asset condition assessment?

iii. What barriers and facilitators influence the adoption of AI technologies in the Western Cape's road asset management framework?

The study's premise is that the process of asset management is evolving as AI technology advances, and while the adoption of these processes in the Western Cape is slow, the barriers and tools that drive this adoption will have an impact on how asset management is done in the future. The unit of analysis describes the focus of the study, particularly whether it will be an individual or organization and the boundaries of the individual or organization that will be studied. Therefore, the Western Cape province is used as a focus to establish a boundary system to explore the context of AI adoption for road asset management. The final steps of the case study design are unpacked in detail below through the theoretical framework.

7.1.2 Theoretical Framework: Diffusion of Innovation Theory

This paper employs Everett Roger's Diffusion of Innovation (DOI) Theory to frame the use of AI technologies in road asset management for condition assessment. DOI theory explains how new ideas, technologies, or practices spread through a social system over time, influenced by factors such as innovation attributes, communication channels, social systems, and time into the management of road assets (Rogers, 1971; García-Avilés, 2020). By focusing on the use and the rates within this province, this paper aims to identify the stages at which the province currently stands and the factors influencing their progress. Using the diffusion of innovation theory as a framework is advantageous because through this framework, the five-stage adoption process can be integrated to better understand the rate at which these new technologies are being implemented. Figure 4 illustrates this process, which includes the stages of knowledge, persuasion, decision, implementation, and confirmation. This paper will assess these stages from data collected from public documents such as reports, manuals, frameworks etc. to gain insight into the use of AI technologies in asset management highlighting key trends and potential barriers.

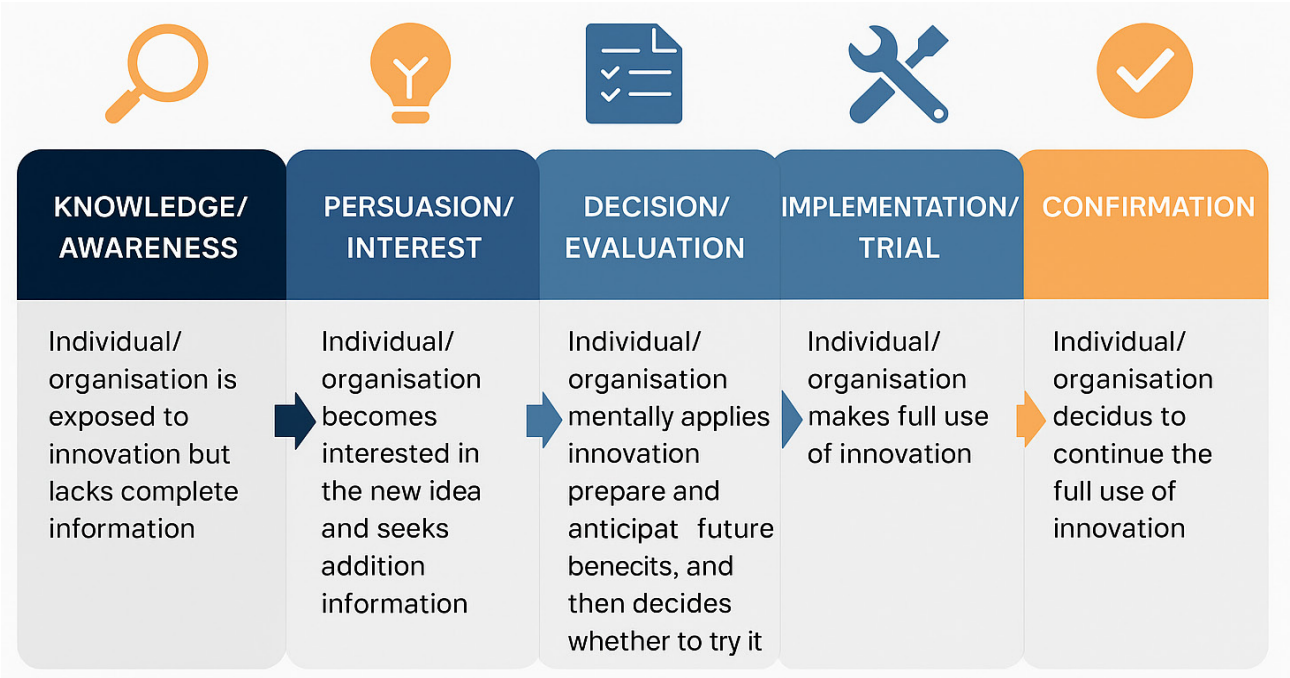

Figure 4: Five-stage adoption process (Roger, 1971)

7.1.3 Data Collection

The study has adopted secondary data where the data was sourced from publicly available records and reports maintained by the provincial government, district municipalities and by the large state-owned entity under the authority of the Ministry of Transport. These data consist of road asset management plans, annual performance report, strategic plan and policy guidelines. It further sourced the data from peer-reviewed journal articles, case studies, and independent research focusing on AI applications in road asset management globally. Key archival data sources spanned between the period from 2014 to 2024, with data collected between December 2024 and January 2025. This data has provided insights into the evolution of asset management practices for road condition assessment and the use of AI technologies within the province.

To ensure accuracy and relevance, data sources were evaluated based on four key criteria:

- Publication credibility (e.g., peer-reviewed status or official government publication);
- Publication date (to ensure recency);
- Alignment with the study's objectives; and
- Internal consistency across datasets.

One of the key limitations of this study lies in its reliance on secondary data. While these data offered official and often comprehensive information, they also carry the risk of reporting bias, such as the underreporting of failures, overemphasis on program success, or omission of contextual challenges. These biases can affect the objectivity and completeness of the data, especially when used to evaluate performance or assess the integration of new technologies such as AI. To mitigate these limitations, the study adopted a triangulation strategy, cross-referencing obtained data with independent research findings, international case studies, and peer-reviewed literature. Where discrepancies were identified, preference was given to sources with transparent methodologies, evidence-based claims, and third-party validation. Additionally, care was taken to examine multiple reports across different years and departments to avoid reliance on a single narrative or dataset.

Nonetheless, the study acknowledges that secondary data cannot fully capture the operational realities, perceptions, and informal practices involved in AI adoption within road asset management. For this reason, future work will incorporate mixed method approach where primary data will be collected through structured interviews and surveys across the province. This approach aims to provide a more refined and ground-level understanding of AI implementation, stakeholder attitudes, and on-the-ground challenges.

7.1.4 Data Analysis

To evaluate the extent to which AI technologies have been adopted within the Western Cape's road asset management framework, this study employed a structured assessment aligned with the five-stage process of the Diffusion of Innovation (DOI) theory: knowledge, persuasion, decision, implementation, and confirmation. Each stage was operationalized using a set of predefined indicators extracted from public documents such as strategic plans, performance reviews, implementation frameworks, and infrastructure policies.

The indicators were defined as follows:

- Knowledge: Evidence of awareness or references to AI or digital tools in strategic documents, training sessions, or preliminary discussions.
- Persuasion: Inclusion of feasibility studies, pilot projects, or budget allocations for AI-related initiatives.
- Decision: Official approvals, directives, or adoption policies formally endorsing the use of AI technologies.
- Implementation: Actual deployment of AI tools (e.g., sensors, machine learning models, or AI-powered platforms) and integration into existing asset management systems.
- Confirmation: Evaluations, performance reviews, or refinements based on the feedback from implemented technologies.

Each district municipality, large state-owned entity under the authority of the Ministry of Transport, and provincial government document was coded based on these criteria using a thematic analysis approach, guided by the research questions and the DOI framework. The data was analyzed by identifying and interpreting patterns, trends, and thematic characteristics related to road asset condition assessment and AI adoption. For each case, the most prominent indicators were used to determine the respective adoption stage. Where multiple indicators were present, emphasis was placed on the most advanced and clearly documented stage. This structured evaluation ensured consistency, traceability, and analytical rigor across all data sources, enabling a clear understanding of the province's overall position within the innovation adoption lifecycle. The findings offered insight into the rate and extent of AI implementation, while also highlighting patterns and outliers, such as the key barriers and enablers influencing adoption. These insights provide policymakers and stakeholders with practical recommendations to optimize the use of AI technologies in road asset management across the Western Cape.

8. ANALYSIS AND FINDINGS

This section of the paper presents the analysis and interpretation of data collected from official reports, manuals, and scholarly journals related to road asset management in the Western Cape province. The findings focused on evaluating the current state of asset management practices, the extent of AI adoption, and the challenges and opportunities associated with integrating AI technologies. A comparative assessment between traditional

and AI-driven approaches is conducted to identify key trends and provide strategic recommendations for enhancing road infrastructure management in the province.

8.1 Current Road Asset Management Practices

The provincial government is responsible for the construction, repair, and upgrading of provincial roads including of 5 district municipalities (Cape Winelands, West Coast, Goerge, Central Karoo and Overberg) road network, aiming to foster positive socio-economic outcomes and establish safe, connected communities. They manage and maintain the road network effectively; the department employs a Road Asset Management System (RAMS). This system facilitates the collection and analysis of data regarding road conditions, traffic volumes, and maintenance requirements, enabling informed decision-making and prioritization of interventions. They utilise STRUMAN platform for both PMS and BMS of road asset management. For reporting issues on provincial roads, stakeholders can contact the Regional Road Maintenance Offices, which serve different district municipalities within the province. According to the Western Cape Road Asset Management Plan 2019/20 to 2028/29 report, it emphasizes the importance of service delivery standards, as outlined in its Service Delivery Charter. This document commits to implementing the Road Asset Management Plan and conducting regular condition assessments to ensure that roads are safe and rideable for users. The Western Cape's current road practices involve a structured and systematic approach to road asset management, focusing on data-driven decision-making, regular condition assessments, and stakeholder engagement to maintain and improve the provincial road network. Similarly, large state-owned entity under the authority of the Ministry of Transport is responsible for the construction, repair, and upgrading of national roads and as well employs RAMS for management of the road asset. They manage their PMS specialized software platforms like dTIMS, which enable data-driven maintenance planning, performance prediction, and lifecycle cost analysis. Furthermore, they use Road Survey Vehicle (RSV) which is a custom-equipped survey truck fitted with advanced instruments that measure and record road condition data while traveling at normal traffic speeds and data collected gets uploaded into dTIMS. Notably, the City of Cape Town also utilizes dTIMS for their PMS, however, road data collected manually through consultant deployment.

8.2 Evaluation of AI Technology Use in Road Asset Management

The status of AI adoption in the Western Cape's road infrastructure asset management was assessed using the DOI framework and the findings are as shown in Table 4.

Based on the available reports, the provincial government, its district municipalities, and the City of Cape Town are primarily positioned in the persuasion and decision stages of the DOI framework concerning the use of AI in road asset condition assessment. While there is clear awareness of AI’s potential and a commitment to developing guiding frameworks, no practical applications or pilot projects have yet been implemented and no publicly available empirical evidence or documented AI-related pilot projects. In contrast, the large state-owned entity under the authority of the Ministry of Transport has advanced to the implementation stage, operationalizing technologies such as RSVs, automated road condition monitoring, and predictive maintenance modelling within their dTIMS-supported Pavement and Bridge Management Systems. Although these tools are not formally classified as AI, they possess AI-aligned capabilities, including data-driven forecasting, risk-based decision-making, and lifecycle cost analysis, effectively positioning the large state-owned entity under the authority of the Ministry of Transport closer to full AI integration within its asset management practices.

Table 4: Findings of Western Cape status as per DOI framework

Stages of DOI Framework	Findings on Provincial and District Llevel	Findings on National Level
Knowledge Stage (awareness & understanding)	The provincial government has developed the "Guardrails for Artificial Intelligence in the Department of Infrastructure" position paper, highlighting AI's potential in road infrastructure management. The Road Network Management Branch Road Asset Management Plan 2019/20 to 2028/29 report, provides a comprehensive view of the current state of road infrastructure assets, indicating an awareness of the need for advanced management tools.	The large state-owned entity under the authority of the Ministry of Transport has long acknowledged the value of advanced data-driven systems, implementing a Road Asset Management System (RAMS) using technologies like RSV (Road Survey Vehicles), LiDAR, and automated data capture systems that form the foundation for AI-based predictive models.
Persuasion Stage (interest & evaluation)	The DOI's position paper discusses AI's role in optimizing resource allocation and public safety through predictive maintenance models, indicating growing interest in AI technologies.	The large state-owned entity under the authority of the Ministry of Transport operational strategies and use of predictive modelling within dTIMS for PMS suggest a sustained interest in AI-enhanced decision-support, particularly in areas like performance prediction and budget optimization.
Decision Stage (commitment & planning)	The DOI's position paper outlines the need for policies and frameworks to regulate AI implementation, reflecting a commitment to integrating AI into road infrastructure management.	The large state-owned entity under the authority of the Ministry of Transport has incorporated AI-aligned functionalities into existing systems like dTIMS and automated data capture tools, showing clear operational planning towards AI-supported asset management
Implementation Stage (trial & adoption)	While the provincial government recognizes the potential for AI-driven predictive models, no current applications or pilot projects are noted in available reports, indicating the province remains at an early stage without AI implementation.	The large state-owned entity under the authority of the Ministry of Transport is at the implementation stage through its advanced use of systems like dTIMS combined with high-speed RSVs, LiDAR, and automated data analytics – foundational elements for AI-supported predictive maintenance and decision-making
Confirmation Stage (sustainability & scaling Up)	The Western Cape provincial government including its district municipalities have not yet reached this stage, as ongoing evaluations and policy developments are necessary to determine the scalability of AI solutions in road infrastructure asset management.	The large state-owned entity under the authority of the Ministry of Transport continues to refine its use of advanced data systems, though full AI adoption is progressive. Scaling up AI functionalities within RAMS is a logical next step as data infrastructure and modelling capabilities mature.

Challenges like data standardization, AI-specific policy formulation, and resource limitations continue to delay broader adoption at national, provincial and district levels in the province. Nonetheless, the large state-owned entity under the authority of the Ministry of Transport adoption of AI-enabling systems provides a valuable reference for the provincial government and its district municipalities to progress toward implementation. These findings were derived through a desktop review of publicly available reports, technical publications, and policy documents. The findings were systematically assessed against the DOI framework. No significant outliers were identified, although a notable trend emerged where the large state-owned entity under the authority of the Ministry of Transport's operational AI-aligned systems contrast with the provincial government policy-

level interest, revealing a clear gap between awareness and implementation readiness in the province.

8.3 Barriers to AI Adoption (Local)

According to available reports, several barriers hinder AI adoption in road infrastructure asset management in the Western Cape. These include the following:

- **Financial constraints** – as AI implementation requires significant investment in infrastructure, software, and skilled personnel.
- **Data-related challenges** – such as poor data quality, lack of integration across systems, and data privacy concerns, also pose significant obstacles.
- **Skills gap** – with a shortage of personnel proficient in AI technologies and data analytics.
- **Regulatory and policy uncertainties** – including the absence of clear guidelines for AI deployment in public infrastructure, further slowdown adoption.
- **Organizational resistance to change** – concerns about AI's long-term sustainability and reliability contribute to slow adoption.

These barriers are highlighted in reports such as the *WCG Department of Infrastructure AI Position Paper* (2024) and the *Road Network Management Branch Road Asset Management Plan* 2019/20 to 2028/29 report.

8.4 Barriers to AI Adoption (Global)

The challenges facing AI adoption in the Western Cape mirror those encountered in other middle-income and developing regions. Similarly to regions in South America and Southeast Asia, barriers such as limited data infrastructure, fragmented asset management systems, resource constraints, and absence of AI-specific regulatory frameworks hinder integration (Arakpogun, et al., 2021). For example, Candelaria, et al. (2021) reported on delayed AI adoption in Brazil's transport infrastructure due to high implementation costs and lack of skilled personnel. While Widodo, et al. (2020) noted similar limitations in Indonesia's road asset management. Conversely, progressive adoption in countries like India and Kenya has been driven by government-funded pilot projects and national AI roadmaps (World Bank, 2021). These global parallels emphasize the need for policy commitment, inter-agency collaboration, and targeted pilot programs in advancing AI integration locally.

8.5 Comparative Analysis: Traditional vs. AI-Based Approaches

A comparative analysis of traditional versus AI-based approaches in road infrastructure asset management reveals distinct differences in efficiency, accuracy, and resource utilization. Table 5 shows the key comparative findings.

While the comparative analysis provides insights into the efficiency, accuracy, and resource utilization differences between traditional and AI-based approaches, the absence of publicly available local AI implementation data limited the inclusion of direct empirical evidence comparisons. However, international studies have demonstrated that AI-based road asset management systems can improve maintenance planning accuracy by up to 30% and reduce reactive maintenance costs by 20-40% (World Bank, 2021; PIARC, 2024). Future research should incorporate quantitative performance metrics from local pilot projects to empirically validate these efficiency gains within the Western Cape context.

Table 5: Comparative analysis of traditional vs. AI-based approaches

Elements	Traditional Approaches	AI-Based Approaches
Data collection and analysis	Rely heavily on manual inspections and periodic assessments, which can be time-consuming and prone to human error.	Utilize advanced AI technologies including IoT sensors and machine learning algorithms to continuously monitor infrastructure conditions, providing real-time data and predictive insights.
Maintenance planning	Often based on reactive strategies, addressing issues as they arise rather than predicting and preventing them.	Enable proactive maintenance through predictive analytics, identifying potential issues before they become critical.
Resource allocation	May lead to suboptimal use of resources due to less precise identification of maintenance needs.	Optimize resource use by accurately pinpointing areas that require attention, reducing unnecessary expenditures.

8.6 Policy Implications

The findings highlight an urgent need for the provincial government to move beyond conceptual discussions and develop formal AI adoption policies and operational guidelines tailored to road infrastructure management. This includes integrating AI-specific frameworks into existing asset management plans, establishing data governance protocols for standardized data capture and sharing, and allocating dedicated funding for pilot projects. Furthermore, the large state-owned entity under the authority of the Ministry of Transport's progressive implementation offers a valuable policy benchmark for provincial authorities. Policymakers should consider collaborative models between national and provincial agencies to accelerate AI integration, ensuring regulatory alignment, capacity building, and long-term infrastructure sustainability. Clear policy direction is essential to transition from planning to practical AI adoption.

9. OPPORTUNITIES, CONCLUSION AND STRATEGIC RECOMMENDATION

The lack of AI adoption in the Western Cape's road infrastructure for asset condition assessments and predictive maintenance strategies presents significant opportunities for improvement. By integrating AI technologies such as predictive analytics, IoT sensors, and machine learning, real-time monitoring, proactive maintenance, and cost reduction can be achieved. Private sector involvement plays a crucial role in this transformation, particularly in providing the necessary technological expertise, funding for pilot projects, and scaling up AI-driven solutions. Public-private partnerships can accelerate AI adoption by sharing risk, driving innovation, and ensuring access to cutting-edge tools and methodologies. To effectively leverage these opportunities, the provincial government must develop a comprehensive AI integration policy to provide regulatory clarity and establish data governance frameworks. Additionally, capacity-building initiatives should be implemented to equip stakeholders with AI-related skills and encourage collaboration among engineers, asset managers, and data analysts. Pilot projects across the region can provide valuable insights and form the foundation for scaling AI adoption. Sustainable funding models, through public-private partnerships and government support, will be essential for ensuring long-term success. The findings of this study are not only applicable to the Western Cape but also offer insights for broader infrastructure management contexts, particularly in other regions facing similar challenges in resource allocation, data governance, and infrastructure maintenance. The lessons drawn from the Western Cape can inform AI adoption strategies in other middle-income and developing regions looking to improve road asset management.

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