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AI-driven predictive maintenance in autonomous public transit systems for smart cities

Umair Ejaz [1,*] and Mohammed Majid Bakhsh [2]

[1] *Senior Software Engineer, United Arab Emirate.*

[2] *Washington University of Science & Technology, USA.*

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Abstract

The introduction of artificial intelligence (AI) in the city transport infrastructure is an innovative initiative on the way to creating resilient and efficient smart cities. Predictive maintenance of autonomous public transit systems is among the most–promising applications The real-time diagnostics and machine learning models are used to predict equipment failures and enhance the optimality of the fleet-wide performance. Compared to conventional maintenance procedures, based on regular inspection checks or afterthought reactions, predictive maintenance employs the in-feed of sensor data, telemetry, and past trends to fore-tell system declining conditions before failures set in. Not only will this switch cause the reduction of operational downtimes but also enhance the safety of passengers, cost-efficiency, and the sustainability of services.

The current paper will discuss how predictive AI will have a defining role in the maintenance management of autonomous fleets of buses, shuttles, and trams within a networked urban setting. It analyzes AI solutions Deep learning, anomaly detection, and digital twin modeling in the context of vehicle-to-infrastructure (V2I) communication and the Internet of Things (IoT). Europe, Asia, and North America case studies are examined to show real-life deployments and quantifiable results. There is also discussion about ethical issues, cybersecurity risks, programs designed to regulate them, and the urgency of transparent AI generalized to reflect the notion of public accountability and smart city governance. The paper has ended with the roadmap of the strategic approach to advance scalable, trusted predictive maintenance systems that can pre-qualify the autonomous subways of the future in the ever-developing city street scenes.

Keywords: Predictive Maintenance; Autonomous Public Transit; Smart City Infrastructure; Artificial Intelligence in Transport; Urban Mobility Innovation; Real-Time Fault Detection; AI-Driven Fleet Management

1. Introduction

Embracing self-driven public transportation is fast transforming how cities seek to mobilize themselves, sustainability, and service delivery. Increasing populations in cities and the necessity to have efficient networks with low rates of emissions are some of the forces pushing smart cities to use artificial intelligence (AI) to enhance all levels of transportation activities. The incorporation of AI-based predictive maintenance, i.e. a preventative approach to identify and stop mechanical breakdowns before they happen, based on real-time data analytics and machine learning algorithms, is one of the most important, but complicated elements of this change.

In the classical systems of transit, maintenance normally occurs on a predetermined basis (preventive) or a break-down system (reactive). Both methods are limited: preventative maintenance may mean unessential changes of parts and high

* Corresponding author: Umair Ejaz

expenses, whereas reactive maintenance will have a risk of major failures and interruptions of services. The inefficiencies associated with current methods of maintenance are broken down using predictive maintenance, which can learn based on past and real-time data readings of a system including sensor output, system logs, temperature changes, and vibration signatures, and can identify anomalies and wear trends. Predictive maintenance is even more crucial in the autonomous form of public transport, where there are no drivers, and the redundancy of the system should be high.

Smart cities exploit the highly networked digital environment in which the public transit system is networking with cloud and IoT devices, vehicle-to-vehicle (V2V), and vehicle-to-infrastructure (V2I) communication systems. In this networked space, predictive AI systems will have the ability to assess the set health of various sub-systems (electric motors, braking systems, battery modules, and navigation sensors) across entire fleets in real time. As an example, edge AI applications can run onboard, thereby allowing diagnostics processing and alert generation locally to limit latency and avoid placing a load on central servers.

Innovations in the field of AI over the recent years, specifically convolutional neural networks (CNNs), recurrent neural networks (RNNs) as well as graph neural networks (GNNs) enable predictive models to capture complicated spatiotemporal auto-dependencies in vehicle behavior. This also enables more than failure detection, component life span can be predicted as well as efficiency of repair routines enhanced. Furthermore, digital twin technologies' virtual models of real-world systems allow predictive modeling with integrity since they allow testing various wear and tear simulations in silico long before they occur in the real world.

Some pilot programs have already begun showing the promise of such a solution across the world. Maintenance strategies (powered by AI) are carried out in electric autonomous shuttles and buses in such cities as Singapore, Helsinki, and Phoenix. The results of these initiatives are being realized in rational terms: better mean time between failures (MTBF), fewer maintenance expenses as well as more fleet uptime.

Nevertheless, the strategy of AI application in this area is not that simple. There are still critical challenges concerning data quality, model interpretability, cybersecurity, and regulatory compliance. Autonomous systems require very low error rates, and any incorrect prediction may jeopardize the safety of passengers and the confidence of the population. It is additionally focusing on making sure that the AI decisions in its public services are clear, fair, and auditable particularly where they are dealing with safety-critical applications.

These issues are reflected in this article, where the presented structure of the study of AI-based predictive maintenance frameworks introduces individual providers to autonomous public transit systems. It will look at the technological enablers, practical deployment strategies, policy implications and predictions regarding this paradigm. In such a way, the paper will add to the existing body of knowledge regarding the ways smart cities might create sustainable, scalable, and ethically acceptable transportation models with the help of AI.

2. Smart Cities and the Role of Autonomous Transit Systems

The next step in the evolution of urban space, known as smart cities, implies the usage of digital technologies, data-driven decision-making, in-time monitoring of the infrastructure, and the optimization of the services offered to the masses. Transportation also becomes the focus of this framework not as a utility but as an intelligent network that is dynamic with the capacity to improve mobility, minimize emissions, and improve the quality of life in a city. The focus of this innovation is autonomy in public transportation which presents an idea of driverless buses, electric shuttles, and interconnected vehicles with low human dependence.

Contemporary smart cities rely on well-established networks of the Internet of Things (IoT), 5G, edge technologies, and a centralized data system. These technologies make it possible to communicate in real time amongst the infrastructure, vehicles, and control centers. The presence of features like adaptive traffic lights, automatic drives, and mobility-as-a-service (MaaS) incorporated into the systems contributes to more than mere convenience and delivers efficiency and safety on a larger scale. These improvement measures are also sustainable since they would save on fuel, carbon emissions, and traffic.

The movement towards autonomous fleets has several advantages, including lower operation costs, optimized shipping routes, and availability of continuous services. Nevertheless, there is a complicated nature of issues that arise in this transition. In contrast to man-operated cars, driverless cars operate based on a system comprised of multiple sensors, actuators, and AI computation procedures. This requires advanced surveillance of system elements such as lidar, radar, battery systems, and drive-by-wire systems, all of which can be deteriorated as well as attacked through software.

Transforming the maintenance strategies necessitates a paradigm change in the management of these systems in the real-time environment. Conventional strategies of maintenance, founded on a predetermined arrangement or reactionary repair, cannot fit autonomous systems since predictive accuracy and quick diagnostics are necessary features. The fact that software and hardware rely on each other in these vehicles suggests that failure in one may cause a cascade where the failure may cause a shift in the system behaviour or create a hazard to the passengers.

Thus, smart data-based maintenance is not a choice but a pillar. Machine learning enables real-time analytics to turn predictive maintenance into an essential alternative to reactive and cycle maintenance to ensure that transit agencies detect problems in advance and prevent them before they result in service disruptions. As an example, vibration pattern of electric motors or braking system thermal data can be analyzed to predict the imminent breakdown. These measures also increase the life of the assets to achieve total cost of ownership and prevent premature replacement of parts and limit labor time.

Table 1 Comparison of Traditional vs Autonomous Transit Maintenance Approaches

Maintenance Dimension	**Traditional Transit Systems**	**Autonomous Transit Systems (AI-Driven)**
Maintenance Type	Scheduled or reactive	Predictive and real-time
Diagnostic Tools	Manual inspections, checklists	Sensor data, AI algorithms, digital twins
Human Involvement	High	Low to moderate (remote monitoring, automated alerts)
Failure Detection	After breakdown	Before failure (anomaly detection)
Operational Downtime	High due to delays in repair	Low due to early intervention and fault forecasting
Scalability	Limited to technician availability	Highly scalable via centralized AI platforms
Cost Efficiency	Moderate; high risk of unnecessary part swaps	High; focused on performance optimization
Risk Management	Reactive	Proactive and risk-mitigated

Since smart cities continue to expand their autonomous fleets, AI-based predictive maintenance is proving itself as an essential facilitator not only in terms of efficiency, but also in terms of safety, sustainability, and securing trust in the systems that will define how cities work in the future of urban transportation.

3. Predictive Maintenance: Core Concepts and Technologies

Predictive maintenance (PdM) is the future-based mechanism of maintenance which is based on the analysis of data to predict the breaking before it occurs because of the equipment malfunctioning. In contrast to preventative maintenance, which acts based on pre-determined time schedules, or to corse corrective maintenance, which reacts after a breakage has been suffered, PdM is used to continuously survey component health with the help of sensors and telemetry information in addition to becoming aware of defects by utilizing smart algorithms. This is aimed at decreasing unplanned downtime, minimal maintenance costs, and service life of critical system components- particularly in intricate, autonomic transit fleets that work in smart cities.

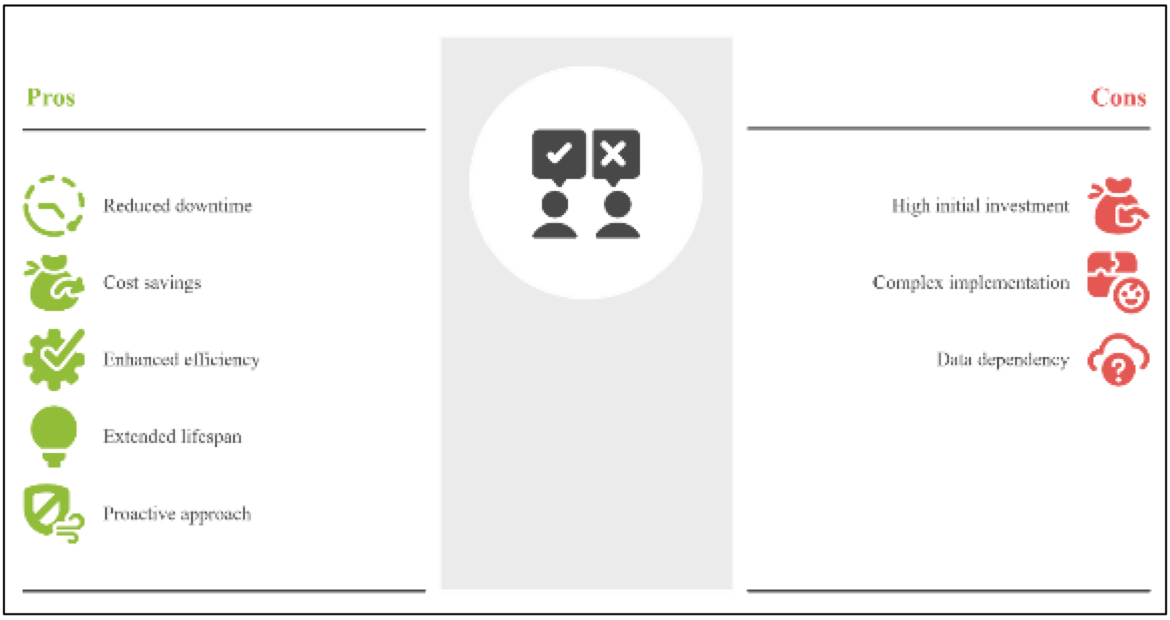

Figure 1 Predictive Maintenance

The main idea of predictive maintenance is based on the analysis of real-time data to find some patterns, anomalies, and preconditions of wear or malfunction. In autonomous systems of public transit, PdM is important because it offers the ability to conduct non-invasive but automated testing of such vital systems as electric propulsion, braking, HVAC (heating, ventilation, and air conditioning) navigation hardware, and communication modules.

AI is a major part of PdM as it allows using streaming and historical data to train systems. There are common AI techniques that are employed such as:

- Machine Learning (ML): The learning models include supervised learning and unsupervised learning to predict trends in the readings provided by the sensors and classify the reading as either normal or unusual. As an example, one can mention Support Vector Machines (SVMs) and Decision Trees that are often applied to the task of fault classification.
- Deep Learning (DL): Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) will be able to handle high dimensional sensor data and incorporate temporal patterns thus can be used in long-term system heath monitoring.
- Edge AI: Edge AI is data analysis with minimal latency at the edge of the embedded systems in the vehicles, deploying the AI models into the devices. This decentralization is critical when in-time decision-making is required, as during a motor overheating alert or sudden power change.
- PdM is also based on an extensive sensor and IoT network that monitors the operation of metrics, such as vibration, temperature, torque, fluid level, battery voltage, and pressure data, to name a few. The inputs are then fed to AI models to generate an alert, or advice if a deviation is found. The opportunity to connect it to the IoT enables it to perform remote diagnostics and process data on both the edge and in the clouds.

We can see the success of PdM on other industries and safety-critical industries to understand how AI-based PdM has evolved. In the case of aviation, say, PdM systems are used to predict failures of jet engines, based on high frequency vibration data, which lowers the maintenance cost by up to 30%. In rail transport, PdM platforms check the wear of wheels, track alignment in real-time, avoiding derailments and improving passenger safety. The examples can be treated as precedents in their scalable imposition to autonomous public transportation systems.

Table 2 AI Models Commonly Used in Predictive Maintenance and Their Applications

AI Model / Technique	Common Application Areas	Advantages in PdM
Support Vector Machines	Fault classification in mechanical parts	High accuracy for small-to-medium datasets
Decision Trees	Rule-based fault prediction	Interpretable models, low computational cost
CNNs	Image/video-based damage detection	Captures spatial patterns in visual data
RNNs / LSTM	Time-series data (e.g., vibration patterns)	Learns temporal dependencies over long sequences
Autoencoders	Anomaly detection in sensor signals	Unsupervised learning of failure signatures
Edge AI (TinyML)	On-device inference for sensors	Real-time analysis with reduced latency

Using these technologies, PdM provides a scaled and smart means of ensuring high-functioning and failure-free transit fleets. The flawless functional integration of sensors, AI, and communication infrastructure prevents the failure of systems and their evidence from being registered and eliminated before turning into expensive or even hazardous complications in public transportation services.

4. AI Integration in Autonomous Transit Maintenance

The incorporation of AI in the maintenance environment of autonomous public transportation systems will emerge as a paradigm shift in the realms of operational efficiency, safety, and sustainability. The maintenance strategies will equally have to be changed to fit the real-time decisions, continuous learning, secure, and automated diagnostics as vehicles become smart and connected. This part examines the complete AI lifecycle, data ingestion to root cause analysis, and enabling items such as digital twins, and edge computing.

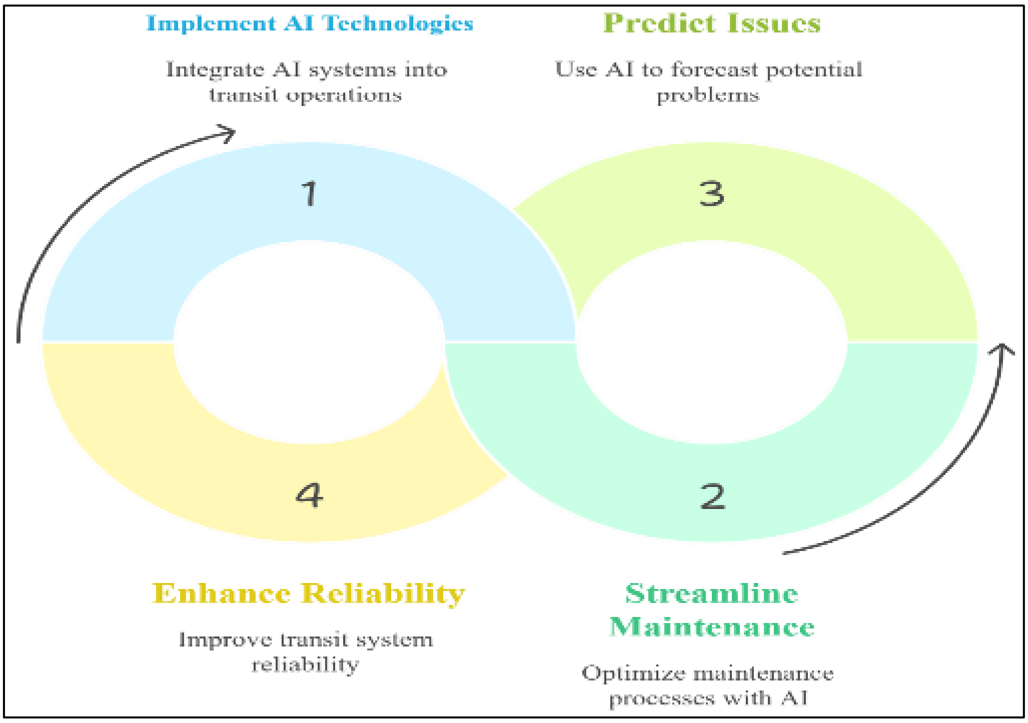

Figure 2 AI Integration in Autonomous Transit Maintenance

4.1. Data Lifecycle: Collection, Processing, and Prediction

The data lifecycle in predictive maintenance (PdM) driven by AI usually starts at the edge, with embedded sensors within components including motors, batteries, brakes, and on-board electronics. These streams of data are passed through to the layers of processing in the cloud or at the edge of the network to be cleaned, and normalized, and the features extracted.

The result is fed into AI models, usually, a machine or deep learning algorithm that can analyze patterns, learn the correlation of sensor signals with previous failures, and generate predictive arguments. These products could be binary failure indicators, risk ratings, suggestions of remaining useful life (RUL) estimates, or scheduled maintenance procedures. The main issues of concern to deal with at this stage are a range of heterogeneous data sources, low-latency equipment, and data integrity.

4.2. Fault Detection and Failure Forecasting

The process of fault detection is meant to detect the anomalies before the actual breakdowns. Under unsupervised learning AI-based methods, systems may identify abnormal operating profiles even where failures are not specifically annotated in the training data. The supervised models might be applied in cases where there is a history of failure records.

Failure forecasting is more than anomaly detection in that it estimates the component's time-to-failure, which the maintenance teams can then plan interventions. Temporal dependencies in telemetry data are modeled with recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models, and other time-series forecasting methodologies. These forecasts increase levels of fleet availability and minimize maintenance charges.

4.3. AI-Powered Diagnostics and Root Cause Analysis

In the event of anomalies being identified or predicted, AI-enabled diagnostics comes in quite handy in determining the nature and origin of the problem. Explainable AI (XAI) methods such as SHAP (Shapley Additive exPlanations) or decision trees help technicians see what features or signals they need the most to predict failure.

Also, root cause analysis (RCA) algorithms can follow faults between subsystems using analyses of dependency graphs or logs of component interactions. Through these systems, engineers can differentiate between symptoms on their surface and deep failures, to reduce downtimes and avoid repetitions. When interfaced with maintenance management software, it may also auto-create work orders or remotely reset when configured within the diagnostic pipeline.

4.4. Role of Digital Twins and Edge Computing in Transit PdM

Making intelligent systems a major part of the population is gaining speed with two advanced technologies:

Digital Twins: A Digital Twin is a model of a physical object (e.g. an autonomous bus or train carriage) with real-time updates based on a live telemetry signal. Digital twins allow simulations of what-ifs and virtual diagnostics and the prediction of the lifecycle. As an example, a digital twin of a braking system will be able to simulate wear under various traffic and weather conditions. This will show a wear risk in advance.

Edge Computing: In mobile applications, delay is important and thus AI models running on the edge have the potential to run inference within the vehicle. This enables extreme speed of decision making, e.g. through automatic deactivation of a vehicle when overheating or sensor error is detected, without needing the time of cloud-side processing.

Collectively, such technologies will guarantee the context-aware, proactive, and autonomous nature of maintenance support imperative to real-time smart urban mobility applications.

4.5. Key Challenges in AI-Based Maintenance Systems

Although AI in the maintenance of transit has benefits, it also has various shortcomings:

Data Sparsity: The high-quality systems do not have failures making training data that cannot be labeled be limited. This is alleviated by the synthesis of data and simulation environments.

Model Drift: The statistics of telemetry records may also change as both the vehicle fleet and deployed hardware change. Learning or retraining models regularly is extremely necessary.

Cybersecurity Risks: Artificial intelligence systems that make maintenance judgments need to be shielded against hacking (e.g., by sensor spoofing or entry and injection of data). Access control, anomaly detection, and end-to-end encryption are essential.

Interoperability: Autonomous transit systems commonly employ the use of various vendors, therefore, standardization of data formatting and communication protocols is difficult.

Implementation: Implementing the high initial cost of setting up the sensors, networks, and compute infrastructure will impede smaller cities and old systems.

Table 3 AI-Driven Predictive Maintenance Workflow in Transit Systems

Stage	Description	Key AI/Tech Tools
Data Acquisition	Real-time sensor data from vehicle components	IoT devices, CAN bus, telemetry
Data Preprocessing	Cleaning, normalization, and feature engineering	ETL pipelines, edge preprocessing
Anomaly Detection	Identifying deviations from normal behavior	Autoencoders, Isolation Forest
Failure Prediction	Estimating time-to-failure or fault likelihood	LSTM, RNN, Gradient Boosting
Diagnostics & RCA	Determining cause of fault, actionable insights	SHAP, decision trees, graph analysis
Decision Execution	Triggering alerts, scheduling maintenance, or taking autonomous action	Edge AI agents, digital twins

5. Infrastructure and Deployment Challenges in Smart Cities

Not just algorithmic smarts, but a solid and well-integrated urban infrastructure is necessary to implement the practice of AI-based predictive maintenance (PdM) in autonomous systems of airport and metro transportation. Although smart cities may be the best setting in which to implement such technologies, in the real sense, complexities may have a way of it not being a smooth process. It is in this section that the multi-faceted issues are addressed including communication infrastructure, heterogeneity of hardware, the interoperability of systems, and barriers brought about by institutions.

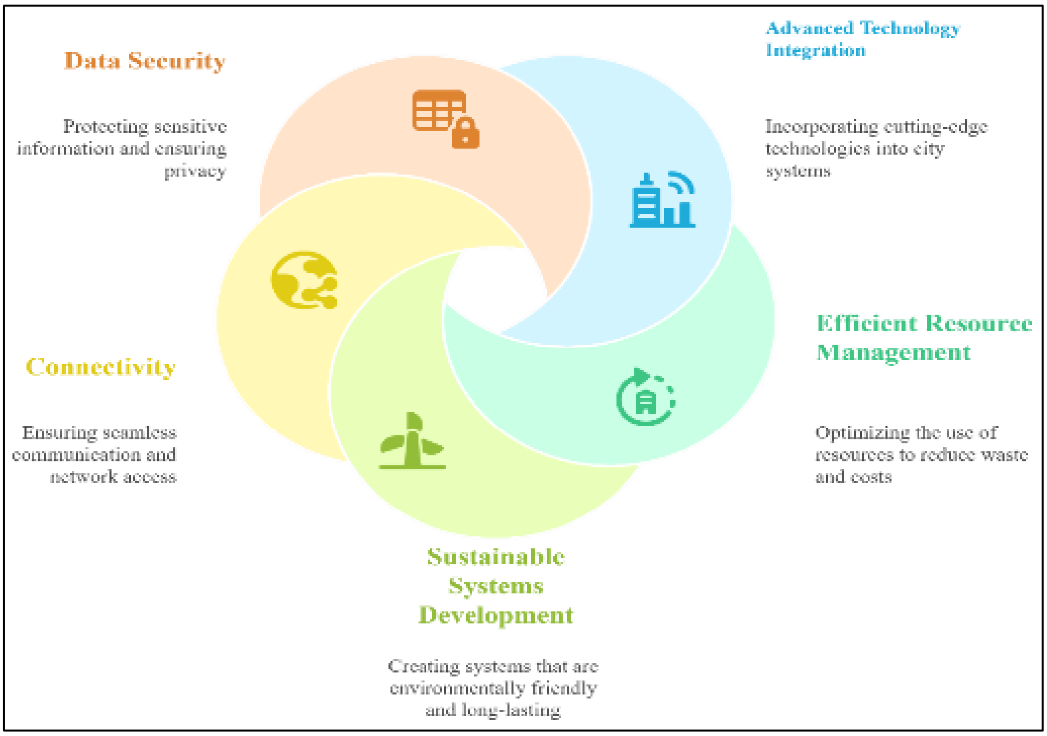

Figure 3 Challenges in smart city development

5.1. Connectivity and Latency Constraints

The key to realizing real-time predictive maintenance in fleets of autonomous vehicles is high-speed and low-latency connectivity. The 5G networks and Vehicle-to-Everything (V2X) communicational procedures are also anticipated to provide real-time data transmission among vehicles, edge computing devices, and cloud servers. Yet, complete 5G coverage is spotty in most areas, generating uneven results.

Due to network congestion caused by dense urbanization, signal interference, and physical obstructions (i.e. buildings, tunnels), latency or data loss can dramatically affect PdM functions. As an example, failure to alert on anomalies promptly can lead to the failure of critical tasks in operational windows. Edge computing can address at least some of these problems, by recording the inference near the source, but continues to require reliable backhaul connectivity to periodically update and monitor the remote site.

5.2. Fleet Diversity and Hardware Standardization

Heterogeneous fleets Heterogeneous fleets are the typical solution used in smart cities, which includes autonomous buses, shuttles, tram services, and other service vehicles, with various hardware specifications, sensor distributions, and maintenance requirements. Such heterogeneity in terms of hardware poses a big challenge to the adoption of AI.

The performance of AI models may suffer when using telemetry of a single vehicle type to predict the behavior of a different type because it is not generalizable. On a similar note, the fact that diagnostics and sensor interfaces are not the same creates challenges in implementing shared data collection and processing streams. The variety requires one of two things model specialization based on classes of vehicles or the creation of flexible, robust AI structures that can learn to consume and normalize a variety of input forms.

5.3. Interoperability Between AI Systems and City Transport Networks

The AI-based maintenance system needs to be conveniently integrated into the overall mobility system of the city, involving transit control centers, maintenance scheduling, and city-wide optimization of traffic efficiency. This has to be done through interoperability protocols and data standardisation between systems and vendors.

Nonetheless, there is a tendency of proprietary technologies and closed APIs which hinder integration endeavors. As an example, an AI fault detection module implemented on a third party electric bus could not present maintenance warnings in a form that the city could ingest into its legacy asset management platform. Also, coordinating across systems is made even more complicated in cases where public-private mobility ecosystems (e.g. ride-sharing platforms that abide by different governance regimes) need to be integrated.

5.4. Policy, Regulatory, and Funding Bottlenecks

Although AI-PdM systems have already passed the technological threshold, regulatory systems and means of funding frequently follow. The use of data in Smart city projects should also conform to data protection regulations like the General Data Protection Regulation (GDPR) in the European Union or other data-protecting regulations in other jurisdictions, particularly in situations that involve personally identifiable information, such as to the logs of vehicles or passengers.

In addition, governmental procurement procedures, low budgets, and political lethargy could impede the deployment of AI infrastructure. Public-private partnerships (PPPs) have potential problems, which are often characterized by misaligned incentives and lack of transparency, undefined responsibilities in case of failure of the AI systems.

Cities also have to walk the ethical path of issues related to algorithms decision-making like it is possible to simplify stop an automobile automatically by results of an algorithm without considering the potential cause or effect. These uncertainties require the existence of multi-stakeholder governance, clear audit trails, and legislative models that are receptive to newly found AI capabilities.

Table 4 Key Infrastructure and Institutional Challenges in AI-Powered Transit Maintenance

Challenge Area	Description	Example Consequences
Connectivity & Latency	Inconsistent 5G/V2X coverage and transmission delays	Missed failure alerts, delayed autonomous response
Fleet Diversity	Different vehicle types and sensor arrays	Incompatible models, need for retraining
System Interoperability	Lack of standard APIs or data formats across platforms	Fragmented maintenance workflows
Regulatory Compliance	Unclear policies on AI decisions and data privacy	Legal liabilities, deployment delays
Funding & Procurement	Bureaucratic inertia and budgetary constraints	Limited infrastructure upgrades, slower adoption

6. Real-World Examples and Emerging Solutions

Although predictive maintenance (PdM) in automatized public transportation systems is currently a growing segment of AI use, there are some examples of an innovative solution deployed by prominent cities and entities. All of these practical implementations can serve as a further lesson to other smart cities that are interested in minimizing operating costs, and asset life, and enhancing safety using smart maintenance systems. Among the important examples, specific startups and vendors, and other notable insights, observed across regions via the existing deployments, will be summarized.

6.1. Singapore: AI-Enhanced Transit Reliability

Singapore The Land Transport Authority (LTA) of Singapore has been on the frontline in adopting predictive maintenance in its Mass Rapid Transit (MRT) and buses. Working together with ST Engineering and Siemens Mobility, Singapore has created AI systems that study vibration sensors, brake heat signatures, and hydraulic pressure to predict the failure of a component in real-time. The Smart Maintenance Management System (SMMS) follows thousands of parts at a time and does maintenance planning on the fly considering forecasted failures thus decreasing the use of scheduled maintenance by a fixed time.

LTA had reported through this system a 30 percent reduction in unscheduled outages which also showed an increment in Mean Time Between Failures (MTBF) in various lines. These findings show the potential of AI to sustain the quality of service in high-demand transit networks with a reduction of overall maintenance costs.

6.2. Los Angeles Metro: AI-Powered Fleet Management

Los Angeles County Metropolitan Transportation Authority (Metro) has undertaken a prediction analytics program to control its huge size of buses and rail network. Metro installed a sensor-based PdM system in more than 2,000 buses by collaborating with an analytics corporation, Uptake. This system records the real-time stream of data on engines, transmission, and onboard subsystems, and submits it to the analysis of the models based on machine learning of Uptake.

During the initial year, Metro has noticed a 12 percent decrease in road calls and an increase in the scheduling efficiency of maintenance workers. Notably, the project led to the importance of clean and properly labeled data as a condition of the correct predictions. This experience underlined the importance of data governance and constant model validation in the delivery of desirable results.

6.3. Emerging Vendors and Startups in the PdM Ecosystem

A wide range of vendors in the AI-powered predictive maintenance ecosystem is growing fast. Siemens Mobility announced Railigent X, an integrated sensor analytics, edge computing, and AI-based risk-scoring platform in transit vehicles. On the same note, Uptake provides train-specific AI models in the field of public transportation based on contextual data taken through sensor data and maintenance history. SparkCognition and Predikto (acquired by Siemens) are other start-ups that made some progress in dynamic PdM in the direction of anomaly detection and condition-based alerts in connected transit systems. Digital twins, recreating physical assets, are frequently used through these platforms to model long-term mechanical stress and fatigue as part of root cause analysis and long-term planning.

6.4. Lessons Learned and Observed Outcomes

There are some distinct trends in all these implementations:

- Integration and quality of data are very important. Vendors and cities that invested early in the strong data infrastructure are better off.
- Edge computing is promising to solve the problem of latency and bandwidth constraints, especially with mobile transit assets.
- Management needs to be changed. Social issues may also contribute to project success or failure, with human factors acting as a possibility to either lead a project into success or failure. Issues considered to be human factors include the training of the operators and the trust that stakeholders may have in AI-based recommendations.
- Scalability is still an obstacle. The most common situation is that the projects begin as piloting and they have to cover interoperability and funding to expand to the city-scale.
- These lessons remind us that AI-PdM is more than just an upgrade in technology, and a change in the maintenance philosophy; this change also involves aligning tools, data, policies, and people.

Table 5 Summary of Predictive Maintenance Implementations in Global Smart Cities

City / Agency	Technology Used	Key Vendor(s)	Results / Impact
Singapore (LTA)	Smart sensors + ML (SMMS)	ST Engineering, Siemens	30% reduction in unplanned downtime
Los Angeles Metro	AI analytics on engine/telemetry data	Uptake	12% fewer road calls; better scheduling
Berlin (BVG)	Real-time diagnostics with edge AI	Railigent X (Siemens)	Improved fleet utilization & diagnostics
Dubai RTA	AI-driven monitoring of tram systems	SparkCognition	Faster fault detection; pilot expansion
Helsinki Transport	Predictive alerts for electric buses	Predikto / in-house	Maintenance delay reduced by 25%

7. Strategic Roadmap for AI-Powered Transit Maintenance

An autonomous (yet fully human-controlled) public transit predictive maintenance ecosystem based on artificial intelligence needs to be implemented strategically and intentionally by implementing not just single technologies. Urban settlements will be forced to embrace an integrated infrastructure anchored on the concept of scalability, resilience, and trust; the three tenets of the current smart operation of transit. Scalability will make sure that AI programs, initially used as pilot projects, can be scaled alike to entire transit systems without affecting performance and price accessibility. The idea of resilience is the process of constructing systems that can withstand sensor malfunctions, cyberattacks, and data anomalies. The operational staff and the population will only trust the AI decision systems when they can see through them, and as long as they can prove that AI has enhanced safety and reliability.

Of this roadmap, one of the most important elements is the design of the technology stack, especially when selecting between cloud-based or edge-based systems. This is because, through cloud computing, there is centralized storage along with model training ability due to which it can provide powerful insights based on aggregated city-wide data analysis. Nevertheless, edge computing is crucial in real-time processing and low-latency responses, particularly in the case of mobile assets such as buses and trains. The one we would ideally want is a hybrid one with edge devices undertaking an instantaneous diagnostic, the cloud doing long-term learning, model retraining, and fleet-level coordination. Data governance should also be considered in this two-layer structure so that it follows the data privacy standards and is interoperable with older systems.

Of equal interest is the transformation of the transit workforce. With the increased role of AI systems performing diagnostic and decision-making tasks, human employees have to be retrained to oversee AI devices, extrapolate the conclusions made by the AI, and handle exceptions. Predictive maintenance does not exclude human technicians, it changes their job description to proactive asset optimization rather than reactive troubleshooting. To this end, upskilling programs, technical AI maintenance-related certifications, and practical training in such technologies as digital twins and sensor diagnostics will play an important role. Simultaneously, the human-in-the-loop approach should be preserved, particularly, in such decision areas as passenger safety, and service disruptions.

Lastly, collaborative governance is mandatory in making AI-powered predictive maintenance successful. Cities and municipal governments, transportation agencies, vendors and suppliers of technology, cybersecurity experts, and regulatory agencies should collaborate on the principles, best practices, and similarities in investment priorities. A major role of the public-private partnerships (PPPs) is to fund the innovation process, but lessen the risks upfront, involved by the government. Also, it should create national frameworks of AI mobility and urban AI testbeds to accelerate learning across sectors enhance the transfer of AI models across cities, and generate a feedback loop to push the iterative enhancement of predictive models.

Essentially, the strategic roadmap towards AI integration in transit repair has to be built on a system level, where technical architecture, policy, and human factors need a leveled balance with cross-sectoral cooperation. Only this holistic approach will allow smart cities to use the capabilities of AI to the fullest in a safe, efficient, and sustainable future of public mobility.

8. Ethical, Safety, and Regulatory Considerations

With AI becoming a part of the predictive maintenance of autonomous transportation, the need to address ethical, legal, and regulatory aspects becomes inevitable. In addition to the technical functionality, sustainability deployment depends on the attendant confidence and legal responsibility on the part of people. Key points that are discussed in this section include liability, transparency, data privacy, and adherence to international standards.

8.1. Liability in Autonomous Failure Events

Mechanical failures in traditional transit systems are normally based on human error, lack of proper maintenance, and manufacturing defects. Nevertheless, as AI-driven autonomous systems make both predictive and operational decisions, the liability process gets complicated. If a self-driving car does not respond to predictive maintenance warnings and results in an accident or some form of service failure, the source of culpability may be spread out among any number of parties, whether it be the software developers, the system integrators, the transit agencies, or even third-party data providers. The legal system of most nations is not yet properly positioned to distribute the liability in the AI value chain, particularly within multi-vendor situations. Consequently, smart cities need to promote the development of regulatory sandboxes and insurance options for AI-enhanced decision-making about transport infrastructure.

8.2. AI Transparency and Explainability in Safety-Critical Systems

Autonomous transit systems powered by AI cannot remain black boxes—especially when failures could endanger human lives or disrupt critical public infrastructure. Explainability is a growing demand from regulators and stakeholders, who must understand why an AI model failed to detect or act on a fault. Explainable AI (XAI) frameworks, such as SHAP (Shapley Additive exPlanations) or LIME (Local Interpretable Model-Agnostic Explanations), are now being embedded into predictive maintenance algorithms to provide interpretable justifications for maintenance predictions and decision thresholds. Transparent logs of model behavior, maintenance alerts, and follow-up actions must be auditable in real time to meet safety expectations.

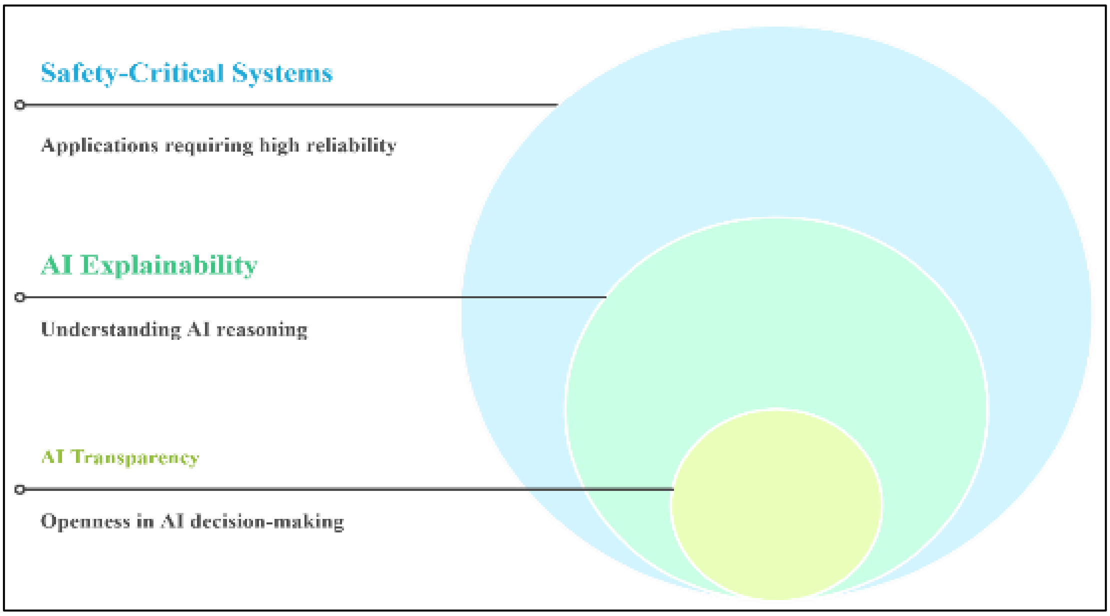

Figure 4 AI transparency and Explainability

8.3. Citizen Data Privacy and Consent

Predictive maintenance often depends on large-scale data collection, including environmental sensors, vehicle telemetry, passenger loads, and even biometric readings in some cases. However, data privacy remains a central concern. Citizens must be protected from misuse or over-collection of data, particularly when AI systems begin integrating facial recognition or location tracking for transit optimization. Public transit agencies must follow data minimization principles, obtain explicit user consent where required, and ensure compliance with regulations such as GDPR (Europe), CCPA (California), and NDPR (Nigeria). Moreover, data anonymization techniques and on-device processing via edge AI can reduce exposure risks and bolster citizen confidence.

8.4. Regulatory Frameworks and International Standards

The deployment of AI in public transportation must align with internationally recognized standards and best practices. The International Electrotechnical Commission (IEC) and International Organization for Standardization (ISO) have published relevant standards such as:

- ISO/IEC 22989 for AI system risk management
- ISO/TS 22149 for AI in intelligent transport systems
- ISO 26262 (originally for automotive functional safety) adapted for autonomous urban mobility
- IEEE 7000 series for ethical AI development and lifecycle governance

In addition, national transport ministries are gradually issuing AI policy frameworks focused on mobility safety, ethical AI deployment, and algorithmic accountability. Ensuring full compliance with these evolving standards is not only a legal imperative but also a key enabler of cross-border technology transfer and trust in AI-powered transit systems.

Smart cities must, therefore, embed ethical foresight, legal clarity, and regulatory alignment into every stage of their AI-based predictive maintenance strategies. Ignoring these considerations can lead to public backlash, service discontinuity, and legal disputes—threatening the very promise of intelligent mobility infrastructure.

9. Future Directions and Innovations

The landscape of AI-driven predictive maintenance in autonomous transit systems is evolving rapidly, driven by breakthroughs in adjacent technologies and an expanding vision for smart cities. While current deployments focus on fault detection and maintenance scheduling, future innovations aim to transform transit systems into self-monitoring, adaptive, and collaborative ecosystems. This section outlines emerging directions that are poised to redefine predictive maintenance in the years ahead.

9.1. Integration with Autonomous Drones and AI Traffic Management

The fusion of autonomous aerial systems with transit maintenance introduces new possibilities for real-time inspection and monitoring. Drones equipped with high-resolution cameras, thermal sensors, and AI analytics can autonomously inspect overhead tram lines, bridges, and depot equipment—without interrupting service operations. In parallel, AI-powered traffic management systems can dynamically adjust signal timing, reroute vehicles, and optimize fleet usage based on maintenance priorities and predictive failure alerts. This integration fosters proactive maintenance coordination, reducing downtime and enabling just-in-time resource allocation for repairs and servicing.

9.2. Emergence of Self-Healing Systems

A promising innovation in smart transit is the development of self-healing systems that can autonomously detect, diagnose, and, to some extent, correct faults without human intervention. These systems rely on redundant architectures, fault-tolerant algorithms, and real-time reconfiguration capabilities. For instance, if an AI system predicts imminent failure in a component, the system can shift workloads, adjust mechanical operations, or trigger remote overrides to minimize disruption. Such systems will be foundational to fully autonomous maintenance operations, where human involvement is minimized to oversight and strategic intervention.

9.3. Federated Learning for Fleet-Wide Intelligence

Most current AI models for predictive maintenance rely on centralized data training, which can be resource-intensive and raise privacy issues. Federated learning offers a transformative approach by allowing AI models to be trained across multiple distributed devices (e.g., autonomous vehicles) without sharing raw data. This means each unit in a fleet can contribute to model improvement while preserving data locality and privacy. Over time, federated learning enhances model generalization across diverse operating conditions, making AI predictions more robust across different city regions, climates, or vehicle types.

9.4. Cross-City AI Model Collaboration

Smart cities worldwide are increasingly recognizing the value of cross-border collaboration in AI model development. Shared frameworks, open-source datasets, and model benchmarks enable cities to learn from one another and accelerate innovation without duplicating efforts. Collaborative platforms like AI4Cities and Open Mobility Foundation are already laying the groundwork for interoperable AI solutions. The future will likely see federated AI networks where cities pool anonymized insights from their fleets, enabling faster detection of systemic issues, broader trend recognition, and coordinated responses to evolving threats or maintenance demands.

In conclusion, the next wave of AI innovation in predictive maintenance will be characterized by autonomy, collaboration, and adaptability. These trends will elevate transit infrastructure from reactive support systems to resilient, intelligent ecosystems, capable of learning, evolving, and optimizing themselves in near real-time. Cities that prepare for this convergence of technologies will not only lead in mobility innovation but also set the standard for sustainable urban operations in the 21st century.

10. Conclusion

As smart cities evolve, the demand for resilient, efficient, and autonomous public transportation systems continues to rise. Predictive maintenance powered by AI represents not just an operational upgrade but a strategic shift in how transit infrastructure is managed and sustained. By enabling proactive fault detection, real-time diagnostics, and data-informed decision-making, AI transforms maintenance from a reactive cost center into a critical enabler of reliability and performance in urban mobility systems.

The strategic value of integrating AI into autonomous transit maintenance extends well beyond technical optimization. It reinforces urban resilience, reduces environmental waste through optimized resource usage, and enhances commuter trust in the dependability of smart transit. By leveraging tools such as machine learning, edge computing, and digital twins, cities can preempt system failures, reduce service disruptions, and maximize fleet availability. Additionally, AI-based insights contribute to improved policy-making and investment planning, aligning technology deployment with long-term sustainability goals.

Looking forward, the emergence of federated learning, self-healing mechanisms, and cross-city AI collaboration underscores a future where public transit is not only smarter but self-sustaining. As cities begin to treat transit systems as living, learning networks—capable of adapting to change and optimizing themselves—the blueprint for a truly autonomous, scalable, and climate-resilient mobility infrastructure becomes a tangible reality. Governments, innovators, and transport authorities must act collaboratively and decisively to operationalize these advancements, ensuring that AI-driven predictive maintenance becomes a cornerstone of future-ready smart cities.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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