

From Data to Policy: AI- Based Predictive Technologies for Urban Mobility and Air Quality Governance

Abstract

Air pollution in cities has been a major problem, and road transport is a major contributor to nitrogen dioxide (NO₂) and particulate matter (PM). LEZs have become a mainstream regulatory intervention, especially in Europe, but the effectiveness of these strategies is limited by their fixed geographical boundaries, slow feedback and their poor sensitivity to evolving urban dynamics. New developments in Digital Twin (DT) technologies provide a platform to approach adaptive, real-time governance of urban air quality through continuous sensing, predictive modelling and data-driven decision support. The present paper has provided a systematic analysis of the technological and Governance underpinnings needed to facilitate DT-driven LEZs. It investigates the purpose of sensing infrastructures and data structures, and machine learning, computer vision and algorithmic traffic models such as microscopic car-following models that convert raw urban data into useful environmental intelligence. In the review, these technologies are also placed in the larger framework of urban data governance, smart-city preparedness, and adherence to the European General Data Protection Regulation (GDPR). The main strength of this paper is the formulation of an integrated framework that connects perception, mobility modelling, emissions estimation, and policy enforcement in a consistent set of DT-supported LEZ ecosystem. The synthesis of technological innovations and institutional and legal aspects guides the paper to offer advice on the implementation of equitable, scalable, and empirically supported interventions to address air quality in European cities and outline important directions of future cross-city benchmarking and standardisation in the research field.

Keywords: Digital Twins; Low Emission Zones; Urban Air Quality; Smart Cities

1. Introduction

1.1 Background: Low Emission Zones and the Limits of Static Governance

Air pollution has always been one of the most lasting environmental and social health issues of modern cities. Road transport is well-known in urban environments to be the largest source of nitrogen dioxide (NO₂) and a significant origin of particulate matter (PM_{2.5}), especially in highly populated corridors and street canyons where dispersion is not possible. The long-term exposure to such pollutants has been associated with respiratory and cardiovascular diseases, premature deaths, and higher health care expenses, and governments have been progressively implementing even stricter regulations to reduce the effects of traffic-related releases [1]. One of the most important policy instruments introduced to help overcome this challenge in Europe is the Low Emission Zones (LEZs). LEZs will decrease the concentrations of pollutants in the environment by limiting or discouraging high-emitting cars, relying on their emission results or fuel types in favour of cleaner cars and alternative transportation methods. Experience with LEZs in cities like London, Berlin, Milan, and Paris has shown that LEZs and more stringent forms, such as the Ultra Low Emission Zone (ULEZs) and Clean Air Zone (CAZs), have had a quantifiable effect on roadside NO₂ and PM concentrations, as well as behaviour change in vehicle ownership and mobility patterns [2].

Although there have been such successes, conventional LEZs are essentially constrained by their fixed structure and reactive rule of governance. The majority of LEZ applications are based on a set of permanent geographical positions, a pre-set vehicle category, and slow or bundled sensor measurements. Mechanisms of enforcement are not usually related to real-time traffic processes, weather, or temporary changes in pollution. Consequently, LEZs usually do not prevent environmental degradation but only react to it when thresholds have already been exceeded. Such a deficiency in the ability to respond to time and anticipate results limits the applicability of LEZs in complex and rapidly shifting urban settings, in which the level of emissions, congestion, and exposure can change dramatically over short time spans.

1.2 Digital Twins as a Paradigm Shift

The appearance of Digital Twin (DT) technologies presents a radical redesign of the approach to the design, surveillance, and enforcement of urban air quality and mobility policies. Digital Twin may be described as a moving, data-oriented virtual model of a physical system that is constantly modified with real-time exchanges of data. Digital Twins in an urban setting combine heterogeneous data streams such as traffic sensors, air-quality sensors, meteorological sensors, and spatial data and coordinates into a single city-wide computational model. In contrast to conventional monitoring frameworks that can deliver a retroactive glimpse of the environment, Digital Twins can help cities transform into non-living but adaptable urban frameworks. DTs enable policymakers to examine the what-if conditions of the situation, predict the pollution

incidents, and quantify the effects of other interventions prior to their implementation in the real world through constant sensing, real-time analytics, and predictive simulation. More importantly, this paradigm shift is supported by three capabilities that are dependent on each other: perception, prediction, and automation.

The concept of perception is defined as the capacity to see urban systems at both high spatial and temporal resolution, which is becoming more and more possible with the development of computer vision, multimodal sensing, and object-level tracking. Prediction is the application of machine learning and algorithmic models to forecast traffic behaviour, emissions, and dynamics in air quality in different conditions. Automation bridges the gap with decision-support systems, or even autonomous control systems, able to modify policies, including LEZ boundaries, enforcement severity, or traffic signalling, based on projected results. This conceptual development is shown in Figure 1, which compares the traditional implementation of LEZ, which involves a set of rules and slow feedback, with the implementation of Digital Twin governance, where real-time perception and predictive modelling underlie adaptive and data-driven decision-making.

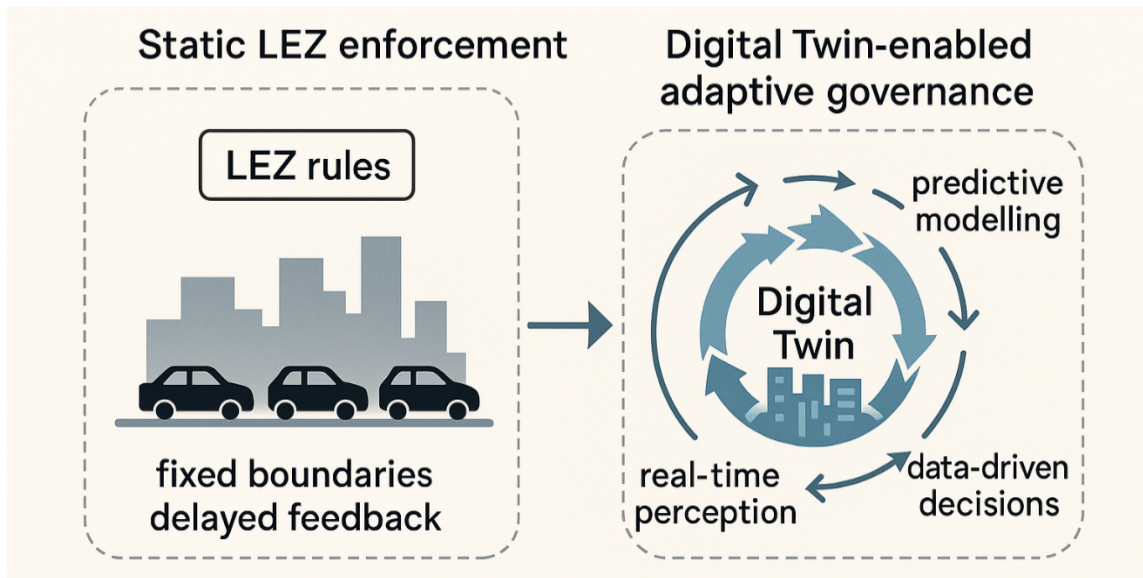


Figure 1: Conceptual evolution from static LEZ enforcement to Digital Twin-enabled adaptive governance

1.3 Research Aim and Scope

It is based on this paradigm shift that the purpose of this paper is to analyze the technological underpinnings that make Digital Twin-led Low Emission Zones a reality, specifically the computational techniques that can convert raw urban data into practical intelligence. In particular, the paper will focus on three fundamental areas of technology:

- (i) Machine learning methods for prediction and decision support,

- (ii) Computer vision techniques for vehicle detection, segmentation, and tracking, and
- (iii) Algorithmic mobility models, including car-following and microscopic traffic models, that link vehicle behaviour to emissions and congestion.

Although the discourse is nailed on the European policy and regulatory framework, especially on LEZ management and data security considerations, the technologies analysed are worldwide and are becoming more locally applicable to air-quality interventions in cities across the world that are in need of implementing adaptive and evidence-based interventions [3]. The rest of the paper is structured in the following way. Section 2 provides the infrastructural and data requirements of LEZs that are DT-enabled, such as sensing and digital city preparedness. Section 3 reviews the use of computer vision-based segmentation and tracking as the perception core of LEZ Digital Twins. Part 4 discusses machine learning and algorithmic mobility models, especially car-following dynamics. Section 5 explains the coupling of perception and mobility models with air-quality simulations and emissions. Part 6 discusses governance, data strategy, and GDPR. Section 7 discusses existing pilot implementations, and Section 8 recognizes the main challenges and gaps in the research. Lastly, Section 9 presents future directions and concludes the paper.

2. Prerequisites for Digital Twin–Enabled Low Emission Zones

The successful implementation of Digital Twin (DT) technology in Low Emission Zones (LEZs) depends on a series of technical, digital, and institutional requirements. In contrast to traditional LEZ applications, which tend to have limited data feeds and fixed rule sets, DT-enabled LEZs are based on real-time, high-resolution data feeds and built-in digital infrastructures. This section defines the underlying specification requirements that can support such systems, including sensing infrastructure, vehicle categorization mechanisms, data inputs, digital city preparedness, and data control frameworks.

2.1 Sensor, Camera, and Scanner Infrastructure

The centre of any DT-enabled LEZ is a well-developed system that provides real-time data concerning vehicle activity, emissions, and the environment. Regulatory compliance and long-term trend monitoring. Fixed air-quality monitoring stations are still vital, and they normally have a measure of the following pollutants: NO₂, PM_{2.5}, PM₁₀, O₃, and CO₂. Nevertheless, their sparse spatial distribution restricts their capability to resolve micro-scale pollution dynamics in complicated cities [4]. To overcome this shortcoming, most cities are now augmenting fixed station arrays with mobile sensing platforms on taxis, buses, or municipal fleets. These mobile sensors have high spatial coverage and allow for detecting temporary pollution hotspots along the key corridors and in the canyons of streets. Simultaneously, visual and ranging sensors such as high-definition (HD) cameras, Automatic Number Plate Recognition (ANPR), LiDAR, and radar are essential in car detection, classification, and follow-up. These sensing modalities are combined to create the perception backbone of DT-enabled LEZs that allow tracking of emission and

mobility patterns in real-time. Table 1 provides an overview of the principal sensor types utilized in DT-enabled LEZ systems, the variables that these sensors are able to measure, their spatial resolution, and their applicability to enforcement and modelling.

Table 1: Sensor types, measured variables, spatial resolution, and relevance to LEZ enforcement

Sensor Type	Primary Variables	Spatial Resolution	Core LEZ / DT Function
Fixed air-quality stations	NO ₂ , PM _{2.5} , PM ₁₀ , O ₃	Low (city-scale)	Regulatory compliance and model calibration
Mobile air-quality sensors	NO ₂ , PM _{2.5} , CO ₂	High (street-level)	Hotspot detection and real-time exposure mapping
HD traffic cameras	Vehicle presence, speed, lane position	Very high	Vehicle detection, segmentation, and trajectory extraction
ANPR cameras	Vehicle identity, entry/exit time	High (zone boundaries)	LEZ compliance and automated enforcement
LiDAR / Radar sensors	3D geometry, speed, motion	High (lane-level)	Robust tracking and occlusion handling
Traffic detectors	Vehicle counts and flow	Medium	Congestion estimation and traffic modelling
Meteorological sensors	Wind, temperature, humidity	Medium	Emissions dispersion and air-quality forecasting

2.2 Vehicle Typologies and Environmental Labels

The second requirement of DT-enabled LEZs is a stable digital determination of adherence to the emission rules by vehicles. In Europe, the access regulations of vehicles are often grounded in the Euro emission standards that classify vehicles by the allowable emission levels of NO_x, PM, and CO₂. Such standards are implemented in the form of local labelling (e.g., Crit’Air stickers in France, Ultra Low Emission Zone (ULEZ) in London, Clean Air Zone (CAZ) in various cities in the UK) [5]. These classifications should be converted into machine-readable formats to be automatically associated with detected vehicles in case of DT-enabled enforcement. It will demand the merging of vehicle registration databases, ANPR systems, and Digital Twins. Correct vehicle typology between cars, vans, buses and heavy goods vehicles, types of fuel and types of emissions are also necessary, not only to fulfil compliance inspections but also to model classes based on emissions and assess exposure.

2.3 Data Requirements

In addition to sensing and vehicle recognition, DT-enabled LEZs rely on a wide variety of data sources to aid real-time analytics and predictive modelling. The data related to traffic are vehicle counts, speeds, acceleration, and micro-trajectories that are needed in congestion analysis and microscopic emissions estimation. These mobility datasets have to be supplemented with vehicle-specific characteristics, including the class, engine type, and emission standard, in order to implement differentiated policy responses. The environmental data also enriches the DT by taking meteorological variables such as wind speed and direction, temperature, and humidity that have a strong impact on pollutant dispersion. Besides that, street-canyon effects and terrain variations in exposure are to be modelled by using urban morphology data, including building height, street width, and land-use patterns [6]. By enabling heterogeneous datasets to be combined, DT-enabled LEZs can transition to high-resolution, street-level environmental intelligence, as opposed to gross averages.

2.4 Digital Foundations of the City

Sensing and data are not useful without a sufficient digital base to combine, process and analyze information on a large scale. The cities that have known smart city platforms and urban data lakes are more likely to implement DT-enabled LEZs since they can use known data pipelines, interoperability models, and governance forms. However, in contrast, most municipalities are still using relatively disconnected systems of legacy, where traffic, environmental, and administrative data are handled separately. One of the major architectural choices is the balance between cloud and edge computing. In the case of cloud infrastructures, scalability and sophisticated analytics can be achieved at the expense of latency and data sovereignty. Compared to edge computing, it allows real-time perception and enforcement applications to undertake low-latency processing very close to the data sources. Figure 2 demonstrates the digital preparedness of DT-enabled LEZ implementation, which includes physical sensing and connection, as well as data integration, analytics and governance layers.

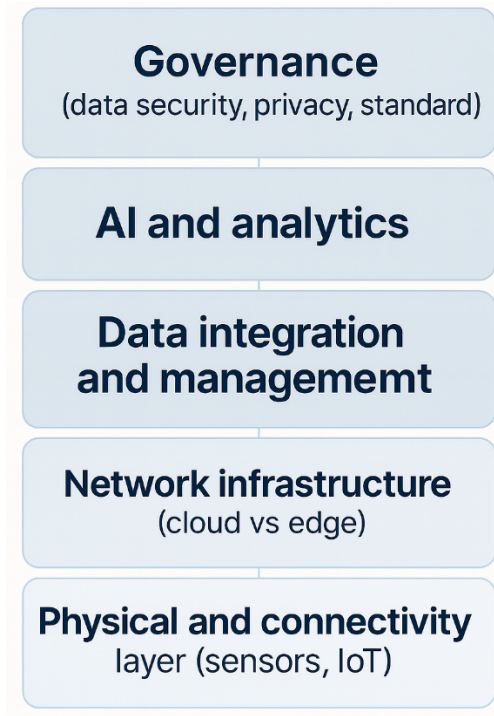


Figure 2: Digital readiness layers required for DT-enabled LEZ deployment

2.5 Data Silos and Storage

Lastly, data silos in organisations and technical systems serve as a serious obstacle to the implementation of DT-enabled LEZ. Traffic, environmental, enforcement and health-related data are frequently owned by various municipal departments or external vendors, and data is often stored and interoperable among various systems. Vendor lock-in also negatively affects flexibility because proprietary data formats and closed platforms make cross-system interoperability and scalability more difficult [7]. To overcome these challenges, it is necessary to implement open standards, interoperable architectures and articulate data governance models that specify ownership, rights of access, and responsibilities. In the absence of these, the full potential of Digital Twins to enable adaptive, evidence-based governance of LEZs cannot be achieved.

3. Computer Vision for LEZs: Segmentation, Detection, and Tracking

3.1 Why Computer Vision Is Central to LEZs

Computer Vision (CV) has emerged as a core technology for Digital Twin-enabled Low Emission Zones (LEZs) because it allows the main method of monitoring, detecting, and tracking vehicles in complex cities. Proper enforcement of LEZ is based on the possibility to unquestionably identify single vehicles, their classification and the state of compliance, as well as their movement within the controlled zones. In the absence of automated visual recognition, policing would still be limited

to infrequent roadblocks, physical inspections, or slow administrative procedures, with a critical restriction of scalability and responsiveness. In addition to enforcement, CV is also important in the modelling of emissions. Vehicle-level perception allows the dynamic mobility variables (speed, acceleration, stop-go behaviour, and lane utilization) that serve as major inputs to the microscopic emissions estimation models. These variables cannot be deduced using the aggregate traffic counts on their own. Consequently, the accuracy of perception limits the fidelity of LEZ compliance monitoring and air-quality Digital Twin simulations directly [8].

3.2 Segmentation as the Backbone of Urban Intelligence

An important difference between CV-based LEZ systems is between object detection and object segmentation. Detectors usually deliver bounding boxes around vehicles, which give localisation of the vehicles coarsely enough to count them or perform simple classification. Segmentation, in contrast, gives each identified object a pixel-level mask, defining its exact spatial extent in the scene. In dense urban traffic scenes, where cars are often in contact, other objects are covering them, or with complicated backgrounds (such as buildings, street furniture, people), then pixel-accurate segmentation is critical. Accurate masks can be used to extract trajectories, track effectively across frames, and the size and position of vehicles relative to road infrastructure can be estimated with confidence. Segmentation in LEZs helps in fine-grain analyses, which extend beyond access control and, therefore, allow congestion, emissions dispersion, and street-level exposure to be finely modelled [9]. As shown in Table 2, the main analytical functions offered by vehicle-level segmentation in LEZ systems can be summarised as follows: it is a cornerstone of urban environmental intelligence.

Table 2: Capabilities enabled by vehicle-level segmentation in LEZ systems

Capability	Key Function	Relevance to LEZs and Digital Twins
Vehicle counting and classification	Identification of vehicles by type	Supports access rules and class-based emissions modelling
Trajectory and speed extraction	Continuous motion tracking	Enables microscopic traffic and emissions modelling
Driving behaviour detection	Stop-go and acceleration patterns	Improves estimation of emissions peaks
Lane-level localisation	Precise spatial positioning	Supports fine-grain traffic management
Occlusion-resilient tracking	Persistent vehicle identity	Ensures reliable enforcement in dense traffic
Cross-camera re-identification	Zone-wide vehicle tracking	Enables longitudinal LEZ compliance monitoring

Vehicle-level emissions attribution	Linking vehicles to emissions factors	Enables high-resolution air-quality simulations
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3.3 Next-Generation Segmentation Architectures

Recent progress on CV has given rise to foundation models that can be effectively used to perform general-purpose segmentation across various visual domains. Architectures based on models like Segment Anything Model 3 (SAM-3) are an instance of transitioning toward integrated systems that entail detection, segmentation and tracking into one, memory-conscious architecture. These models use massive pretraining and multimodal representations to generalise between classes of objects and environmental features. This type of architecture is characterized by the application of dynamic masklet matching, which ensures temporal consistency in the segmentation outputs over video frames. Instead of working on frames one at a time, masklets are transmitted and updated over time, allowing vehicles to maintain constant identities despite occlusions, sudden manoeuvres or partial visibility. Paralleling this mechanism are per-object memory banks, which contain historical visual and geometric features, which allow persistent tracking even across intersections and multi-camera networks [10]. Figure 3 demonstrates a segmentation and tracking pipeline that is based on the principles of SAM-3 but is focused on urban traffic scenes and the LEZ monitoring conditions.

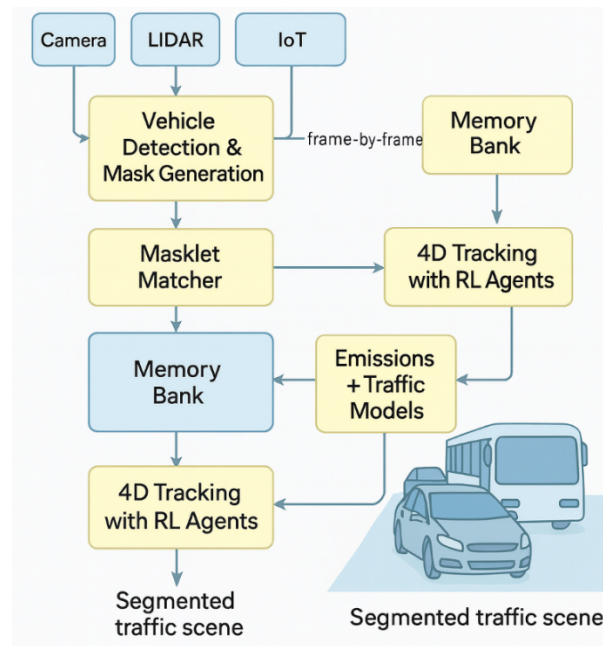


Figure 3: Segmentation and tracking pipeline inspired by SAM-3 architectures for urban traffic scenes

3.4 Multimodal Urban Perception

LEZ Digital Twins Urban perception is becoming more dependent on multimodal data fusion, integrating visual information provided by cameras with depth and geometry information provided by LiDAR and any contextual information provided by IoT sensors. Camera-LiDAR fusion enhances stability in harsh lighting or weather, and also allows for localising vehicles with high precision within the urban environment 3D. Embeddings based on geometry-sensitive representations of such multi-modal inputs enable perception models to more effectively differentiate vehicle types and to be spatially consistent across viewpoints. Cross-camera and cross-modal alignment ensures further system scalability by allowing vehicles to be monitored as they change camera field of view or sensing modality. This feature is especially needed by large LEZs across districts, where implementation and emissions modelling need sustained vehicle identities within space and time [11].

3.5 Challenges in Urban Computer Vision Deployment

Although much has changed, the implementation of the CV systems in LEZ applications has a few challenges. Segmentation accuracy and stability of tracking can be compromised by dense traffic conditions and high-frequency occlusions at junctions or curbside parking areas. Weather inconsistency, such as rain, fog and low-light situations, also makes visual perception difficult and requires strong sensor fusion mechanisms. Systems-wise, a large number of CV pipelines are required to be run with very tight latency requirements, especially in an edge device implementation to enable real-time enforcement or traffic management. A key challenge is maintaining the model complexity and computational efficiency, particularly in incorporating a high-resolution segmentation, multimodal fusion, and persistent tracking over the city scale [12]. They must be dealt with to make sure that CV-driven perception can be trusted to sustain the adaptive and predictive aspirations of Digital Twin-enabled LEZ governance.

4. Machine Learning and Algorithmic Mobility Models

4.1 Role of Machine Learning in Digital Twin–Enabled LEZs

Machine Learning (ML) is at the core of allowing Digital Twins (DTs) to go beyond descriptive representations of urban systems and instead make predictions and act in response to them. Conventional traffic and air-quality monitoring systems, applied in the context of Low Emission Zones (LEZs), mainly characterize historical or present scenarios based on cumulative metrics (p.e, average number of vehicles, hourly pollutant levels). Though this kind of descriptive analytics can be used to report and comply, it is inadequate to predict short-term peaks of pollution or to dynamically revise policy interventions. Using ML-based techniques allows DTs to acquire nonlinear relationships between traffic behaviour, meteorological conditions, and emissions in a real-time manner. Being constantly fed on large volumes of urban data streams in real time, ML

models can predict the near-term traffic conditions, emissions rates, and exposure risks, and thus assist proactive LEZ control. Such predictive advantages are especially relevant in large cities, where minimal shifts in traffic movement or driving behaviour can result in disproportionate rises in NO₂ and PM_{2.5} concentrations [13].

4.2 Car-Following Models in Urban Traffic

Car-following models are at the heart of microscopic traffic modelling, and they explain how individual vehicles change their speed and acceleration based on the traffic. LEZ is greatly applicable to these models since the instantaneous driving behaviour, which includes acceleration, deceleration, and idling behaviour among vehicles, has a strong impact on vehicle emissions. Car-following dynamics thus offer a very important connection between traffic movement and emissions production at a vehicle level.

4.2.1 Classical Models

Some of the most popular classical models of car-following include the Gipps model and the Intelligent Driver Model (IDM). The Gipps model concentrates on safety-related constraints, with the vehicles being spaced far enough to prevent collisions during worst-case braking situations. Although useful to model traffic, its discrete-time model may restrict responsiveness to fast behaviour changes. In comparison, the Intelligent Driver Model (IDM) provides a formulation that is explicit and continuous, explicitly involving the trade-off of desired speed, safe following distance, and acceleration behaviour. The IDM expresses vehicle acceleration as:

$$\dot{v} = a \left[1 - \left(\frac{v}{v_0} \right)^\delta - \left(\frac{s^*(v, \Delta v)}{s} \right)^2 \right]$$

Where v is the current speed, v_0 the desired speed, a the maximum acceleration, s the actual gap to the leading vehicle, and s^* The desired dynamic gap is dependent on speed and relative velocity. The creation of stop-go waves, the formation of congestion and peaks of acceleration-induced emissions is realistically reproduced in this formulation, which makes it especially valuable in LEZ-related emissions modelling [14]. Figure 4 shows the dynamics of car-following and the correlation between spacing, speed, and acceleration in urban traffic conditions.

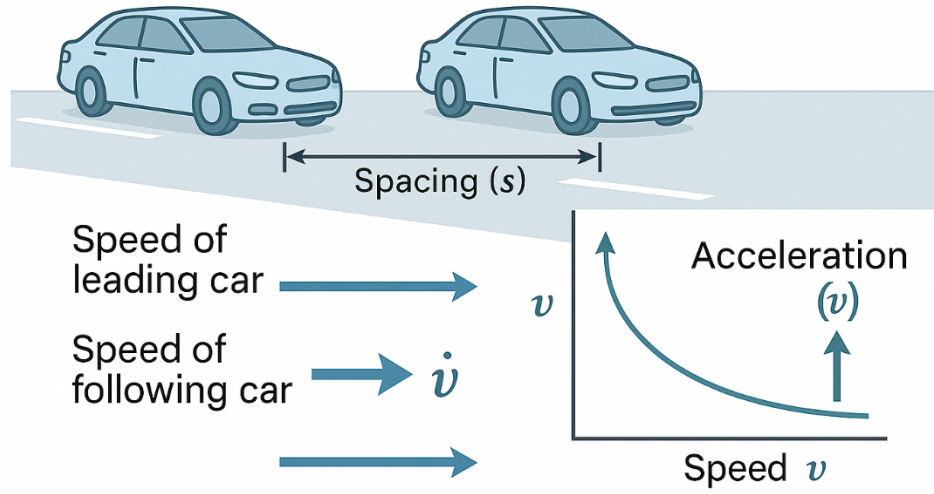


Figure 4: Illustration of car-following dynamics and spacing–speed relationships

4.2.2 Microscopic vs. Macroscopic Modelling

Car-following models are a type of microscopic traffic model that models the behaviour of individual vehicles. Macroscopic models, on the other hand, assume that traffic consists of a continuous flow, where aggregate concepts (including density and average speed) are used to describe it. Macroscopic models are computationally efficient, but they are not accurate enough to represent driving patterns sensitive to emissions, including aggressive acceleration or braking at crossings. Microscopic models are very valuable in LEZ applications. They enable estimation of emissions at the vehicle level, classify driving behaviour, and make it possible to test scenarios with targeted interventions such as dynamic speed limits or selective access restrictions. Consequently, microscopic modelling provides a natural basis of DT-enabled LEZs, even though it requires more computational effort [15].

4.3 Learning-Based Mobility Models

Classic car following models require making pre-determined assumptions about human behaviour, whereas learning based mobility models use data-driven analytical methods to directly model complex behaviour based on observations. Recurrent neural architectures such as Long Short-Term Memory (LSTM) networks and others have been extensively used to predict temporal traffic, acquire dependencies in the speed, flow, and occupancy time series. These models are especially efficient in the context of short-horizon prediction, which justifies proactive LEZ interventions, such as temporary access control or traffic diversion. Graph Neural Networks (GNNs) build upon this ability by modelling urban road networks' topology explicitly. GNNs can model dependencies of space by using intersections (as nodes) and roadways (as edges), predicting traffic at the city scale and preserving network structure. Reinforcement Learning (RL) methods further extend

these models by training optimal driving policies or control policies by interacting with a simulated environment. RL was used in LEZ scenarios to simulate adaptive driving behaviour, traffic design, and congestion management plans [16].

4.4 4D Mobility Modelling

An essential characteristic of DT-enabled LEZs is the ability to integrate mobility data in four dimensions: three-dimensional space and time. 4D mobility modelling is a combination of fragmented vehicle route and time behavioural profiles, creating a high-level representation of urban traffic dynamics. These models include behavioural signatures like stop-go cycles, changes of lanes and queuing behaviour, which are very important determinants of the intensity of emissions. DTs can predict the diffusion of individual driving behaviours through the urban environment to influence pollution levels and exposure by connecting 4D mobility representations to emissions and air-quality models [17]. The integration allows assessing LEZ policies on a fine-grained level, which contributes to enforcement and strategic planning. Table 3 compares classical and learning-based traffic models according to their assumptions, data needs, and applicability to DT-enabled LEZ applications.

Table 3: Comparison of classical and learning-based traffic models for LEZ Digital Twins

Model Type	Core Principle	Key Strength	Main Limitation	LEZ Suitability
Gipps model	Safety-based car-following	Stable and interpretable	Limited behavioural realism	Moderate
Intelligent Driver Model (IDM)	Continuous speed-spacing dynamics	Realistic stop-go behaviour	Requires calibration	High
Macroscopic models	Aggregate traffic flow	Computational efficiency	No vehicle-level detail	Low
LSTM models	Data-driven temporal learning	Strong short-term prediction	Low interpretability	High

Graph Neural Networks	Network-aware learning	Captures spatial dependencies	Higher complexity	Very high
Reinforcement Learning	Policy optimisation via interaction	Adaptive control capability	Training stability	Very high

5. Linking Perception to Emissions and Air Quality

One of the strongest points of Digital Twin (DT) enabled Low Emission Zones (LEZs) is that they can convert small-scale perception of traffic into large-scale estimates of both emissions and air quality. DTs offer a mechanistic connection between mobility behaviour and environmental outcomes because they combine vehicle detection and tracking with computer vision and emissions and dispersion models. The integration can lead LEZs beyond rough compliance inspection to active, evidence-based air quality management.

5.1 Vehicle-Level Emissions Estimation

Instantaneous driving behaviour is very sensitive to vehicle emissions, especially speed, acceleration, and idling patterns. Contrary to aggregate traffic indicators, vehicle-level perception allows the estimation of emissions to be microscopic, which captures the variation of the urban driving environment. In speed- and acceleration-based emissions models, segmented vehicle trajectories are used to calculate instantaneous rates of emissions, which are able to capture peaks related to stop-go traffic, aggressive acceleration, or congestion-related idling [18]. These models are implemented at scale in DT-enabled LEZs, where the profile of each segmented and tracked vehicle is the emissions profile based on the observed movement. This is an especially applicable method in urban settings, where high intersections and crossroads result in very diverse driving patterns. Using the high-frequency data of the trajectory, DTs can generate temporally resolved estimates of emissions that are more precise than estimates relying on average speeds only.

Emission factors based on classes further streamline this process by considering the difference in vehicles and technologies. The emissions characteristics of passenger cars, vans, buses and heavy goods vehicles are also significantly different, especially in terms of NO_x and PM_{2.5}. Combining the vehicle classification results of computer vision pipelines with emission factor databases enables DTs to assign emissions to particular vehicle classes and regulatory categories, including Euro emission standards or local LEZ labels [19]. The ability facilitates differentiated policy interventions, such as enforcement or fleet renewal incentives.

5.2 Pollutant Dispersion Modelling

The evaluation of the air quality impacts does not stop at the estimation of the emissions. DTs should model the emission dispersion in the built environment to determine the impact of traffic pollutants on urban exposure. This is commonly done with the use of Computational Fluid Dynamics (CFD) models, which can model the movement and dispersion of pollutants due to wind, turbulence and urban morphology. CFD models have been noted to be especially effective in the representation of street-canyon effects, where a building geometry can trap pollutants and cause pollutant levels to rise to human-level concentration [20]. Full CFD simulations are, however, computationally expensive and perhaps are not practical to allow real-time uses at the city scale. Consequently, reduced-order or hybrid dispersion models that trade off physical accuracy against computation speed are commonly used by DTs. Such models provide simplified models of airflow and turbulence, based on a calibration with CFD or experimental data, to provide faster predictions but with sensitivity to all important variables, including wind direction and street geometry. Figure 5 demonstrates the theoretical pipeline between segmented vehicle paths and street-level pollution dispersion modelling, indicating that the emission estimates are converted to spatially explicit concentration fields.

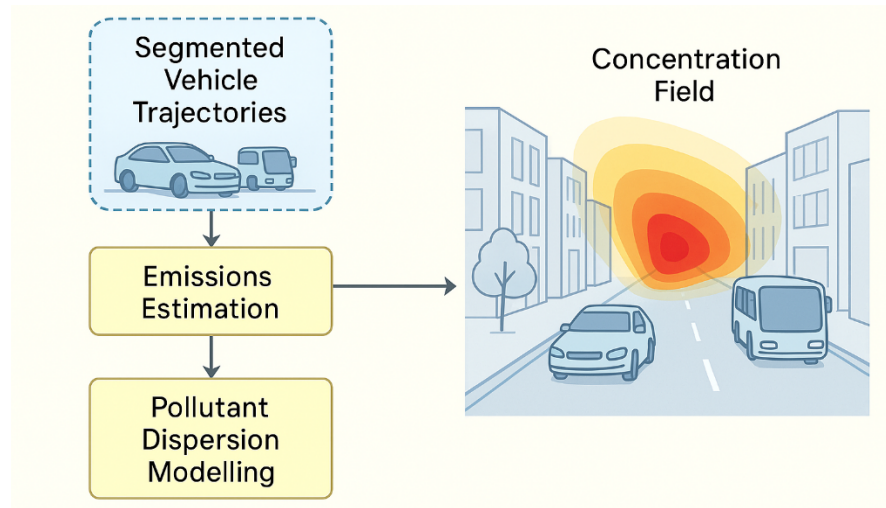


Figure 5: From segmented vehicle trajectories to street-level pollution dispersion modelling

5.3 Real-Time Forecasting

Real-time air quality predictability is one of the most transformative functions of DT-enabled LEZs. By combining meteorological information with emissions generated by traffic, DTs are capable of producing a short-horizon forecast of the pollution levels, most often within 5-15 minutes. Such projections are especially useful in the prediction of the short-lived pollution events due to sudden congestion, bad weather, or traffic accidents. Such forecasting is increasingly supported by machine learning models such as recurrent neural networks and hybrid physics-

informed models. These models can learn temporal patterns in emissions and dispersion whilst including the exogenous factors that include wind speed, temperature, and atmospheric stability. Provided that traffic and meteorological data are integrated, DTs can provide early warnings, suggest mitigation strategies, or change LEZ parameters in advance before regulatory limits are met [21].

5.4 LEZ Compliance and Enforcement Layers

The last tier in the DT-enabled LEZ model converts emissions and air-quality data into governance practices. Responsive rule evaluation systems are implemented to continuously determine whether the conditions that are observed or predicted should justify changes in LEZ operation. This can be the provision of temporary increases of restricted areas, modification of accessibility regulations, or even congestion pricing systems. Enforcement responses may be distinguished in terms of severity and policy goals. Automated warnings, like getting an alert to a driver, or public information dashboards, are a low-intervention strategy designed to change behaviour and provide transparency. Instead, sanctions such as fines or entry limits can be initiated when violations are repeated or when the levels of pollution are causally threatening to human health. Notably, the DT-based systems of enforcement allow basing these decisions on real-time evidence instead of fixed thresholds or past data [22]. DT-enabled LEZs provide a closed-loop of adaptive urban air quality regulation by combining perception, emissions estimation, dispersion modelling, and enforcement logic. This connection can convert LEZs into active, anticipatory tools, which can respond to the dynamic character of city pollution.

6. Governance, Data Strategy, and GDPR

Implementing Digital Twin (DT) technologies in Low Emission Zones (LEZs) is not purely a technical project; it is also influenced by the organization of governance, data management policies, and regulations. Although advanced sensing, machine learning and modelling allow the creation of real-time environmental intelligence, their use is ultimately determined by the manner data are governed, shared and used in public institutions. These considerations are especially relevant in the European setting, where data protection requirements are strict, and the multi-level governance structure is complicated.

6.1 Urban Data Governance

Urban data governance establishes the data collection, ownership, sharing, and stewarding of data within municipal ecosystems. The sources of relevant data in DT-enabled LEZs can be multiple, such as transport authorities, environmental agencies, police departments, mobility operators of private vehicles, and technology vendors. This variety poses data ownership and stewardship issues because tasks associated with data quality, access control and long-term maintenance are frequently dispersed among organisations [23]. The deployment of DT needs to have proper

governance structures, stating who owns which data, who must keep it accurate and under what circumstances information can be shared or reused. In the absence of such visibility, DT platforms will turn into technically advanced and institutionally fragile frameworks. The inter-agency coordination is thus an important precondition. Traffic management centres, environmental monitoring units and enforcement bodies need to harmonise their data practices to facilitate integrated decisions. Cities with a lack of cross-departmental coordination fail to leave pilot projects, because data silos do not allow the creation of a single operational image.

To enable easy access and analysis, increasingly cities are moving to urban data platforms or data lakes that centralise heterogeneous data and offer standardised interfaces to access and analysis. Although these platforms are capable of assisting interoperability, they are also associated with governance concerns of control, accountability, and reliance on outside vendors. To make sure that the DT-enabled LEZs are flexible and transparent, it is necessary to have governance models that allow centralisation but, at the same time, institutional autonomy.

6.2 GDPR Implications for LEZ Digital Twins

The General Data Protection Regulation (GDPR) is an overarching legal framework for the processing of personal data within the European Union. LEZs that use DT often operate on data feeds like vehicle tracks, number plate readers and geolocated sensor data that can directly or indirectly identify individuals. This makes compliance with GDPR a design constraint and not a legal consideration at the margins [24]. Each of the activities related to LEZ must have a legal foundation for processing data. Typical legal foundations are the performance of a task which is performed in the public interest, adherence to a legal duty, or, in a few instances, legitimate interests. Significantly, the enforcement may need more justification than the planning or monitoring use of DT outputs. The difference influences the manipulation of data that can be stored, shared, and taken into action.

The most commonly used approaches to mitigating privacy risks are pseudonymisation and aggregation. DT systems can reduce the identifiability of individuals by decoupling identifiers and behavioural data or pooling information to spatial or temporal clusters to preserve analytical utility. But actual LEZ enforcement is frequently reliant on fine-grain data, which limits the degree of anonymisation which may be used without compromising functionality [25]. There are also restrictions on persistent or excessive surveillance provided by GDPR. Continued surveillance of vehicles by space and time can be regarded as disproportionate unless there is a justifiable public interest purpose and the state is accompanied by such safeguards as limits on purpose and minimalization of data consistency, and high-quality access controls. These limitations force DT designers to be keen on balancing analytical ambition with legal and ethical acceptability. Table 4 summarises key GDPR principles and their implications for DT-enabled LEZ technologies.

Table 4: GDPR principles and their implications for DT-enabled LEZ technologies

GDPR Principle	Implication for DT-Enabled LEZs
Lawfulness, fairness, transparency	Clear legal basis required for data use; citizens must be informed about LEZ data processing
Purpose limitation	Data collected for air quality or enforcement cannot be reused for unrelated purposes.
Data minimisation	Only data strictly necessary for LEZ operation should be processed.
Storage limitation	Personal data must not be retained longer than required for policy or enforcement needs.
Integrity and confidentiality	Strong security, access control, and protection against misuse are mandatory.
Accountability	Authorities must demonstrate compliance and governance responsibility.

6.3 Ethical and Social Considerations

In addition to legal compliance, DT-enabled LEZs provoke greater ethical and social concerns. The issue of algorithmic bias is one of the core issues, especially when machine learning systems are being trained on past traffic or enforcement data that are subject to present-day disparities. Bias models are susceptible to over-targeting certain neighbourhoods, vehicle types or socio-economic groups, thus perpetuating spatial or social injustice [26]. LEZ restrictions tend to affect low-income households more frequently because they are less likely to have newer and lower-emission vehicles. Where DT-facilitated enforcement increases compliance inspections or extends limited areas, these effects may be magnified without compensating factors like exemptions, subsidies, or alternative means of mobility. Social equity must be incorporated into the design of models and policy interpretation in order to have ethical LEZ governance.

Explainability and transparency also contribute to the public trust of DT-enabled systems. Citizens and stakeholders should have the opportunity to know how they make decisions, what information

they apply, and what enforcement measures are taken based on the outputs of the algorithms. Demystifying operations of DT can be achieved through explainable AI-based methods, open dashboards, and participatory design practice [27]. Overall, governance, data strategy, and GDPR issues influence the scope within which LEZs empowered with DT can operate. These dimensions should be addressed to guarantee that technological innovation is transformed into legitimate, equitable and socially acceptable governance of the quality of air in the city.

7. State of Practice and Case Examples

Although the adoption of Digital Twins (DTs) into Low Emission Zone (LEZ) governance is an immature area of research and development, various European cities and industrial projects have advanced beyond theoretical frameworks into practical implementation. These case studies give useful knowledge on the technical feasibility, governance issues, and institutional preparedness of DT-enabled LEZ systems.

7.1 EU Pilot Projects

The Digital Urban European Twins (DUET) project is one of the most visible public-sector projects, and it was financed by the EU Horizon 2020 programme. The objective of DUET is to build interoperable Digital Twin platforms to enable data-driven urban policy-making along several domains, such as mobility, emissions, and land-use planning. The DUET Digital Twin deployed in Athens combines the traffic sensor, air-quality, and meteorological information to recreate the LEZ-related scenarios and evaluate the effectiveness of the traffic regulation policies on the NO_x concentrations. Before making physical city adjustments, policymakers can consider the impact of changing access policies, access enforcement policies, or zone perimeters [28]. The DUET platform in Helsinki helps in providing long-term carbon neutrality by connecting transport emissions to spatial planning and energy information. Although the system does not strictly target LEZ enforcement, it exemplifies how a system of DTs can be applied to assess the implications of mobility policies in terms of emissions in both spatial and temporal scales. These pilots underscore the importance of simulation in a scenario-based, as well as stakeholder engagement, specifically interactive dashboards that can simplify but expose the complex model outputs to non-technical decision-makers.

The Smart London project, uniting transport, environmental, and infrastructure data into a city-wide Digital Twin ecosystem, is also another prominent one. Transport for London (TfL) has a sophisticated air-quality monitoring and forecasting platform that facilitates the management of the Ultra Low Emission Zone (ULEZ). The platform is not a completely self-governing DT; however, it combines real-time traffic, emissions inventory, and forecasting models to guide LEZ enforcement and communication policy [29].

7.2 Emerging Industry Platforms

Simultaneously with the public-sector pilots, more and more industry-led platforms are creating DT-enabled solutions to urban traffic and emissions control. Traffic twins are traffic monitoring systems that use computer vision to recover high-resolution images of traffic flows, vehicle classifications, and vehicle paths using dense networks of cameras and sophisticated segmentation processes. These platforms have been applied to contribute to congestion analysis, emissions estimation and compliance monitoring within LEZ contexts. Another area of emerging technology is taxi-based sensing systems. Cities can capture large areas of space at a comparatively low cost by outfitting ride-hailing or taxi fleets with air-quality sensors. Information obtained through these mobile applications is incorporated into DT environments to optimize pollution maps, hotspot identification, and dispersion model validation. These systems have been trialled in a number of European and North American cities, showing that they can be used in addition to fixed monitoring infrastructure [30].

8. Key Challenges and Research Gaps

Even though Digital Twin (DT) technologies have become more mature and have shown the potential of the concept in Low Emission Zone (LEZ) applications, there are still considerable challenges that limit large-scale implementation and long-term effectiveness. These problems are technical, institutional and research-based based and hence the necessity of integrated improvements in the engineering, governance and policy arenas.

8.1 Technical Challenges

Scalability is one of the main technical issues of DT-enabled LEZ systems. Although pilot-scale studies have demonstrated that real-time perception, modelling, and prediction can be performed at the corridor or district level, when applied at the scale of a whole metropolitan region, they impose significant computational and data management challenges. Continuous processing of high volumes of data is needed in high-resolution computer vision pipelines, vehicle-level emissions estimation, and dispersion modelling, which puts strain on cloud and edge computing infrastructures. Calibration of models is another challenge. Both the classical traffic model and the data-driven machine learning solutions rely on the parameters, which need to be adapted to the local conditions, including driving behaviour, fleet composition, and urban morphology. Poor calibration may result in wrongly estimated emissions or wrongly projected predictions, which affects the credibility of policy. Calibration can be a challenging task, especially over time, with traffic patterns and vehicle fleets changing. Operational deployment is also constrained by real-time constraints. Numerous DT components, particularly segmentation, tracking and forecasting, should have low latency to enable adaptive LEZ enforcement or traffic management. This degree of responsiveness and model accuracy is a vital technical trade-off.

8.2 Institutional and Legal Barriers

Even outside of technical aspects, institutional and legal challenges can be the most significant impediments to the implementation of DT-enabled LEZ. The regulatory inertia may slow the implementation of adaptive governance models because the legal frameworks that are already in place are often structured around fixed rules and ex post assessment. The shift towards the inclusion of real-time algorithm-driven decision-making in the existing regulatory processes necessitates institutional culture, workflow, and accountability structures. The uncertainty of enforcement also makes deployment more difficult. In most jurisdictions, it is not clear if the use of DT-generated information, like planned emissions or performed vehicle behaviour, can form a legal foundation in an enforcement action. This uncertainty tends to position DT systems on the sidelines of operation, thus restricting their influence. The legalization of algorithmic evidence and predictive outputs is thus critical towards transitioning between experimental and ordinary applications.

8.3 Research Gaps

There are still multiple knowledge gaps that restrict the evidence base of DT-enabled LEZ systems. One of the existing gaps is the lack of standardized Key Performance Indicators (KPIs) to assess system effectiveness. Performance cannot be benchmarked, or one implementation can be compared with another between cities, because without no shared measures of emissions reductions, policy responsiveness or social equity performance. Comparative studies across cities are still infrequent, and most studies involving cross-city pilots are done in a single-case study. This reduces the generalisability of the findings and delays transfer of knowledge. Lastly, high-income cities of Europe and North America are the most intensive in terms of DT research and deployment. The fact that it has been limited in the Global South, where the burdens of air pollution are frequently the greatest questions about the issue of technological inequity and accentuates the necessity of scalable, cost-effective, and context-sensitive DT solutions.

9. Future Directions and Conclusions

9.1 Toward Agentic and Self-Adaptive Cities

The intersection of Digital Twin (DT) technologies and highly computerized artificial intelligence is a decisive move toward agentic and self-adaptive urban systems. It is probable that future DT-enabled Low Emission Zones (LEZs) will become a decision-support tool that becomes a semi-autonomous governance system and has the ability to sense, predict, and react to environmental conditions constantly. Cities can make use of AI-based control loops, combining real-time perception, machine learning-based forecasting, and policy implementation layers to respond to exceedances after they happen, instead of proactively regulating traffic and emissions. These systems would be able to dynamically change LEZ boundaries, enforcement strength, or access regulations in response to forecasted levels of pollution, traffic patterns, or weather. As an illustration, a DT might predict a temporary spike in NO₂ due to bad weather and demand in

traffic, initiating a temporary access limit or redistribution of traffic signals. Such adaptive reasoning would make LEZs more than mere regulatory tools by using them as active parts of a larger urban control system and would increase environmental performance and operational efficiency.

9.2 Standardisation and Benchmarking

One of the key facilitators of this future vision is standardisation. The lack of standard data models, interfaces, and evaluation measures makes the implementation of DT-enabled LEZs currently not scalable and not comparable. The open data standards of traffic, emission, and air-quality modelling would align with the current geospatial and smart city architectures and support the interoperability of platforms and jurisdictions. Benchmarking efforts at the EU-wide level would also facilitate knowledge exchange among cities since it would allow systematic comparison of the performance of LEZ. Standardised Key Performance Indicators (KPIs), such as the reduction of emissions, policy responsiveness, equitable enforcement and engagement of citizens, would enable policymakers not only to determine whether LEZs work, but also how and at what price. This kind of benchmarking is necessary to evidence-based policy diffusion, and to prevent disjointed, city-specific responses that are hard to generalize.

9.3 Conclusion

The technological and governance principles of Digital Twin-enabled Low Emission Zones have been discussed in this paper, with a specific interest in machine learning, computer vision, and models of algorithmic mobility. It has demonstrated how improvements in perception by vehicles segmenting and tracking them can be connected with microscopic traffic modelling, emissions prediction and air-quality forecasting to allow a closed-loop system of adaptive urban governance. Similarly, the paper has emphasized the significance of the governance structures, data strategies, and regulatory compliance, especially within the limits of the European data protection framework. The most significant input of this work is the expression of the necessity to combine perception, modelling, and governance in a single DT-LEZ system. Technological innovation is not the only thing we need, but it takes institutional preparedness, legality, and ethical design to realize the benefits. Going ahead, LEZs that are enabled by DT provide a channel into a more equitable, transparent, and data-driven approach to urban air quality. When put into place in a manner that is responsible and inclusive, they will be able to assist cities in meeting climate neutrality and public health goals and adjust to the changing realities of city life.

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