

AI-Driven Digital Twins for Transportation Environments: Integrating Geospatial Scene Synthesis with VOC Exposure and Short-Term Health Risk Modeling

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Abstract

The operational complexity of urban transportation systems increasingly requires computational environments that can represent physical infrastructure, dynamic mobility flows, and environmental stressors in an integrated manner. Digital twins have emerged as promising platforms for coupling sensing, simulation, and decision support, yet many existing implementations remain fragmented across geometric reconstruction, air quality assessment, and public health analytics. This paper presents a system-level analysis of AI-driven digital twins for transportation environments, emphasizing the integration of geospatial scene synthesis with volatile organic compound exposure and short-term health risk modeling. Rather than proposing a single algorithm, the paper examines architectural trade-offs, data infrastructure requirements, model governance mechanisms, robustness conditions, fairness considerations, and deployment constraints. The discussion develops a layered conceptual architecture in which generative geospatial scene synthesis supplies microenvironmental context, while exposure models translate pollutant concentrations into health-relevant indicators across transit modes. Particular attention is given to the challenges of synchronizing heterogeneous data streams, managing uncertainty in AI-generated scene representations, and ensuring that health risk outputs remain interpretable for public agencies. The paper further addresses policy implications related to air quality management, transit ventilation improvements, and the equitable distribution of environmental information. It argues that the value of such digital twins lies not primarily in predictive precision alone, but in their capacity to link spatial representation, environmental monitoring, and health governance within a transparent and maintainable socio-technical system.

Keywords

AI-driven digital twins, transportation environments, geospatial scene synthesis, volatile organic compounds, health risk modeling, urban governance.

1. Introduction

Urban transportation environments are dense socio-technical systems in which infrastructure condition, vehicle operations, passenger behavior, and atmospheric chemistry interact across fine spatial and temporal scales. Digital twins have been advanced as computational counterparts that can represent such systems for monitoring, simulation, and control [1]. The rapid expansion of artificial intelligence has strengthened the ability of digital twins to ingest high-dimensional sensor data, generate missing spatial information, and forecast environmental states [2]. Industrial digital twin practices have contributed lifecycle-oriented modeling traditions that are now being adapted to urban mobility and environmental health

contexts [3]. However, the integration of photorealistic scene understanding with exposure science remains relatively underdeveloped in transportation digital twin research.

This paper addresses that gap by examining how geospatial scene synthesis can be linked with volatile organic compound exposure modeling and short-term health risk assessment in transportation settings. Volatile organic compounds are an important class of pollutants in enclosed and semi-enclosed transit microenvironments, where short-term exposure may produce respiratory irritation, neurological symptoms, or inflammatory responses. At the same time, exposure depends on spatial context, ventilation conditions, passenger density, and the built form of stations and vehicles. A digital twin that merely models traffic flow or air quality in isolation cannot fully capture these dependencies.

The contribution of this paper is system-level rather than algorithmic. It develops a conceptual architecture for integrating generative scene synthesis, pollutant concentration fields, personal exposure estimation, and health risk communication. It also analyzes structural trade-offs, including the tension between model fidelity and computational cost, the challenge of maintaining synchronization across heterogeneous data systems, and the governance demands created by AI-generated environmental information. The paper further considers deployment constraints, sustainability, robustness, and fairness as first-order design requirements rather than secondary concerns.

2. Conceptual Foundations and Related Systems

Urban digital twins extend the industrial digital twin concept to city-scale infrastructures, including transportation networks, buildings, environmental monitoring systems, and public services [4]. Unlike traditional geographic information systems, urban digital twins often aim to couple real-time data with simulation and participatory interfaces. Several city-scale projects have explored citizen feedback mechanisms to improve the relevance and legitimacy of urban digital twins [5]. Participatory approaches have also been proposed to connect technical modeling with local knowledge in urban planning and mobility management [6]. These developments imply that transportation digital twins should not be designed only for expert analysts but also for public agencies, transit operators, and possibly affected communities.

Geometric and semantic representations of the built environment provide the spatial substrate for transportation digital twins. Three-dimensional city models have matured considerably, offering standardized representations of buildings, roads, vegetation, and infrastructure [7]. Yet such models are often static and may lack the view-level detail needed to characterize microenvironmental exposure. Volunteered geographic information has helped to enrich spatial datasets with locally produced observations [8], but data quality and representativeness remain persistent concerns. Urban computing has supplied analytical techniques for fusing mobility, environmental, and social data across city regions [9]. Real-time urbanism further emphasizes the continuous temporal dimension of city operations [10]. These foundations create an opportunity for AI-driven digital twins that can synthesize missing spatial views, model dynamic pollutant fields, and support short-term health risk assessment.

3. Geospatial Scene Synthesis and Environmental Representation

A central challenge in transportation digital twins is the construction of spatially complete and visually coherent representations of complex street and station environments. Mobile mapping, stationary cameras, and open geospatial datasets rarely provide uniform coverage across all areas of interest. Recent advances in geospatially guided diffusion have

demonstrated the possibility of synthesizing mixed-view panoramas conditioned on geographic location and viewpoint context [11]. Such generative methods can fill observational gaps, reconstruct plausible scene details, and support visual inspection of transportation microenvironments without requiring exhaustive physical surveys.

The structural trade-off introduced by generative scene synthesis is significant. Traditional photogrammetric reconstruction offers strong geometric fidelity when source imagery is abundant, but it degrades under occlusion, lighting changes, and sparse coverage. Generative approaches can produce visually plausible scenes from limited inputs, yet they introduce uncertainty that is not easily quantified in geometric or semantic terms. For exposure modeling, this uncertainty matters because ventilation pathways, enclosure geometry, and the presence of emission sources are visually inferred from scene representations. A digital twin that uses synthetic scenes for environmental analysis must therefore carry metadata about generation conditions, data provenance, and confidence levels.

From a system perspective, geospatial scene synthesis should be treated as a component within a larger representational pipeline rather than as a standalone visualization tool. It can support scene completion for transit platforms, bus stops, underground walkways, and roadside environments. When coupled with object detection, semantic segmentation, and thermal or gas sensor data, synthetic scene layers can help identify probable emission sources and occupant locations. However, the use of generative scene content in health-relevant applications requires careful validation against independent observations.

4. VOC Exposure and Short-Term Health Risk Modeling

Volatile organic compounds in transportation environments vary strongly by mode, route, ventilation, and passenger activity. Empirical measurements in subway, bus, and taxi environments have revealed notable differences in VOC concentrations and associated short-term health effects across travel modes [12]. These differences are not solely determined by outdoor air quality; indoor sources, vehicle materials, cleaning agents, fuel emissions, and restricted air exchange also contribute. Exposure assessment therefore requires microenvironment-specific modeling that goes beyond citywide pollutant maps.

Indoor air quality research has consistently shown that pollutant concentrations inside vehicles and stations can differ substantially from ambient levels [13]. The health relevance of short-term exposure is supported by a broad literature linking air pollution to respiratory and cardiovascular outcomes, although much of that literature has focused on longer-term exposures [14]. Short-term health risk estimation can be supported by formal health impact assessment frameworks that translate concentration changes into health endpoints using exposure-response relationships and baseline health data [15]. In transportation digital twins, such frameworks must be adapted to high-frequency transit microenvironments, where exposure durations are short but repeated.

Integrating VOC modeling into a digital twin raises several system-level challenges. First, the spatial coverage of VOC sensors is typically sparse, requiring interpolation or surrogate modeling informed by land use, traffic, ventilation, and building characteristics. Second, chemical mixtures in transit environments are complex, and the health effects of combined VOC exposure are less well characterized than those of common criteria pollutants. Third, personal exposure depends on individual mobility patterns, which may be inferred from travel surveys, smart card data, or mobile positioning but are subject to privacy constraints. A robust

digital twin must therefore represent exposure as a distribution across populations rather than as a single deterministic surface.

5. System Architecture and Data Infrastructure

Scaling digital twins from isolated demonstrations to operational transportation systems requires architectural strategies that address data ingestion, model orchestration, and service delivery. Research on scaling digital twins has emphasized the need to move from artisanal, one-off models to reusable, well-characterized components [16]. The values and challenges associated with digital twin modeling include synchronization, uncertainty propagation, and the maintenance of model validity over time [17]. In transportation environments, these concerns are amplified by the diversity of data sources, including video streams, air quality sensors, transit vehicle telemetry, weather observations, and passenger counts.

A layered architecture is appropriate for integrating geospatial scene synthesis and VOC exposure modeling. At the sensing layer, heterogeneous data are collected from fixed and mobile sensors, with edge processing used to reduce bandwidth and latency in high-frequency video and gas monitoring. At the representation layer, scene synthesis models generate or complete spatial views, while semantic models encode infrastructure elements relevant to pollutant dispersion and exposure. At the analytics layer, VOC concentration fields, exposure estimates, and short-term health risk metrics are computed. At the interaction layer, dashboards, alerts, and policy-facing tools present outputs for decision support.

Service-oriented architectural patterns can support modular deployment across different transit agencies and environmental departments [19]. However, loose coupling must be balanced against the need for consistent data semantics and traceable model lineage. If scene generation models are updated independently of exposure models, the resulting digital twin may produce incompatible representations. System architects should therefore define stable interfaces that allow components to evolve without breaking the overall analytical workflow.

Algorithmic governance is also an architectural concern. The use of AI-generated scenes and health risk estimates can affect public decisions about ventilation upgrades, route management, and travel advisories. Ethical analysis of algorithmic systems highlights the importance of transparency, accountability, and contestability in high-impact applications [18]. These principles should inform the design of logging mechanisms, audit trails, and user-facing explanations within the digital twin platform.

6. Governance, Robustness, and Fairness

Governance arrangements for transportation digital twins must address technical performance, institutional responsibility, and social legitimacy. Reviews of city digital twin potentials have identified the need for clear objectives and stakeholder engagement before technical deployment [20]. In the context of air quality and health, governance also intersects with environmental justice. Spatial analyses of air pollution have repeatedly demonstrated that exposure burdens are unevenly distributed, with disadvantaged communities often facing higher pollutant concentrations [21]. A digital twin that is blind to these disparities may inadvertently reinforce existing inequities.

Robustness is another essential requirement. Transportation sensor networks experience failures, drift, and adversarial conditions. Generative scene synthesis models may produce visually plausible but physically incorrect scenes under distribution shift. VOC sensors may be affected by temperature, humidity, and cross-sensitivity. Health risk models depend on

population baseline data that may be incomplete. A robust digital twin should quantify uncertainty, degrade gracefully under missing data, and provide confidence intervals or qualitative reliability indicators for public outputs. This is particularly important when outputs inform short-term interventions such as ventilation adjustments or health advisories.

Fairness considerations extend beyond exposure disparities to data representation. If sensor coverage is concentrated in wealthy districts or major commercial corridors, the digital twin may underrepresent residential areas and informal transit nodes. If scene synthesis models are trained primarily on specific urban forms, they may perform poorly in older infrastructure or informal settlements. Addressing these biases requires deliberate data collection strategies, fairness audits, and community-based validation. Governance frameworks should specify who is responsible for maintaining data quality, who can access model outputs, and how affected communities can challenge incorrect or harmful representations.

Trusted data spaces and interoperability frameworks have been proposed to support collaborative urban digital twin development across public and private actors [23]. Such frameworks can help prevent vendor lock-in and promote shared data standards. However, interoperability alone does not guarantee responsible use. Health-relevant digital twins should also align with established air quality guidelines and public health standards [22]. The combination of technical standards and public health norms provides a basis for evaluating whether model outputs are actionable and defensible.

7. Deployment, Sustainability, and Policy Implications

Deployment of AI-driven transportation digital twins must account for long-term maintenance, energy consumption, and institutional capacity. Smart city and infrastructure research has emphasized that digital systems should be evaluated not only by their analytical capabilities but also by their operational sustainability [24]. Generative scene synthesis and continuous environmental monitoring can be computationally demanding. Lifecycle assessments of digital twin infrastructure should include model training costs, data storage growth, sensor maintenance, and hardware refresh cycles. Without such assessments, digital twin initiatives may become financially or environmentally unsustainable over time.

From a policy perspective, integrated VOC exposure and health risk modeling can support several regulatory and planning functions. Transit agencies can use digital twin outputs to prioritize ventilation improvements in stations with high pollutant accumulation. Municipal health departments can issue targeted advisories during pollution episodes. Urban planners can evaluate how street canyon geometry, bus stop placement, and traffic management affect microenvironmental exposure. Environmental regulators can use modeled exposure distributions to inform compliance monitoring and health impact assessments. These uses require that models be interpretable, well documented, and accessible to non-specialist decision makers.

Policy implications also include data protection and public participation. Mobility data used for personal exposure estimation may reveal sensitive information about individuals. Digital twin governance must therefore incorporate privacy-preserving methods, data minimization, and transparent consent processes. Public agencies should create mechanisms for community input on monitoring priorities and model assumptions. If digital twins are developed only through technical procurement, they may lack the institutional trust needed for sustained use. A better approach is to embed digital twin development within broader air quality and transportation planning processes.

Sustainability and equity should be treated as design constraints rather than afterthoughts. A transportation digital twin that requires continuous high-resolution video collection from all public spaces may generate privacy and energy costs that exceed its benefits. A more sustainable design might combine targeted high-fidelity sensing with lower-cost proxy data and periodic model recalibration. The goal is not to maximize data volume but to achieve sufficient representational fidelity for the health and planning decisions being supported.

8. Conclusion

This paper has examined the system-level integration of geospatial scene synthesis and VOC exposure modeling within AI-driven digital twins for transportation environments. The analysis highlights that the core challenge is not merely connecting two technical models, but designing a coherent socio-technical system that can represent spatial context, environmental stressors, population exposure, and health risk in a transparent and maintainable manner. Generative geospatial scene synthesis can provide the microenvironmental context often missing from traditional air quality models. VOC exposure modeling can translate pollutant concentrations into health-relevant indicators. However, both components introduce uncertainties that must be managed through careful architectural design.

The paper has argued that transportation digital twins should be assessed according to trade-offs among fidelity, cost, robustness, fairness, and sustainability. Governance arrangements, data infrastructure, and policy integration are as important as model accuracy. Future work should develop standardized validation protocols for synthetic scene content, systematic uncertainty propagation methods across exposure and health models, and participatory governance mechanisms that connect digital twin outputs to community health priorities. By treating digital twins as evolving institutional infrastructures rather than static predictive tools, transportation agencies can better align AI-driven environmental modeling with public health and urban sustainability goals.

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