Urban Artificial Intelligence in Mobility Infrastructure: Lessons for Just and Inclusive Cities

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Artificial Intelligence is increasingly embedded in urban mobility and emergency response systems, where real-time decision-making, infrastructure coordination, and public safety converge. This article examines Urban Artificial Intelligence (Urban AI) through the domain of traffic management and emergency mobility, using these systems as a strategic entry point for analyzing broader questions of governance, equity, and resilience in AI-enabled cities. The paper develops a theoretical framework that distinguishes among cognitive, data-driven, and hybrid Urban AI models, highlighting

1. Introduction

Today's cities are increasingly governed by invisible computational frameworks–layered systems that shape not only the movement of people and goods but also the everyday operations that make urban life possible. These digital layers do more than orchestrate urban functions; they actively reshape how cities are managed, experienced, and understood. As urban environments become more complex and data-intensive, computational intelligence has emerged as a central mechanism for interpreting, predicting, and intervening in urban processes. This convergence has given rise to what is increasingly described in the literature as Urban Artificial Intelligence (Urban AI).

Urban AI represents a substantive shift beyond earlier smart city paradigms, which primarily emphasized sensor deployment, data aggregation, and rule-based system optimization. While early smart city initiatives often relied on descriptive analytics and pre-programmed automation,

how each approach shapes urban knowledge production, operational performance, and accountability. This framework is grounded through three U.S.-based case studies: AI-enabled emergency vehicle preemption in Fremont, California; AI-assisted subway infrastructure monitoring in New York City; and AI-driven signal coordination for emergency routing in Seattle. Together, these cases illustrate how Urban AI systems are deployed in real-world contexts to enhance efficiency, safety, and resilience. The analysis demonstrates that while Urban AI can significantly improve urban operations, its long-term legitimacy depends on integrating principles of equity, transparency, environmental responsibility, and participatory governance. The article concludes by arguing for integrated Urban AI models that balance technical effectiveness with democratic oversight, positioning Urban AI as a critical component of just, resilient, and inclusive urban futures.

contemporary Urban AI systems incorporate machine learning, predictive modeling, and adaptive decision-making to support real-time urban governance. In this sense, Urban AI extends smart city logics from monitoring and efficiency toward learning-based, anticipatory, and interventionist systems. As Caprotti (2024) argues, these developments not only transform how urban systems operate but also generate new metaphors and experiences of urban life, reshaping how cities are inhabited and governed. While Urban Artificial Intelligence is applied across a wide range of urban domains, this study focuses specifically on urban traffic management and emergency mobility infrastructures. These systems represent one of the most mature, data-intensive, and governance-sensitive areas of Urban AI deployment, where the societal consequences of algorithmic decision-making are immediate and measurable (Varış Husar et al., 2025; 2023). By examining AI-enabled traffic control, infrastructure maintenance, and emergency routing, the paper uses mobility systems as an analytical lens to explore broader issues of accountability, equity, and institutional legitimacy in Urban AI, rather than claiming comprehensive coverage of all urban AI applications (Mostafavi et al., 2025).

From an operational perspective, Urban AI systems such as AI-driven "city brains" centralize heterogeneous urban data streams and apply predictive analytics to actively manage citywide functions. A prominent example is Hangzhou's City Brain, which integrates real-time data from cameras, sensors, and traffic authorities to optimize traffic flow and emergency response across the metropolitan area (Atlas of Urban Tech, 2025;

Wired, 2018). While such cases demonstrate measurable performance improvements—particularly in mobility and response times—they also foreground deeper questions about governance, accountability, and power embedded within AI-mediated urban systems. The growing integration of the Artificial Intelligence of Things (AIoT)—combining physical sensors, digital twins, cloud platforms, and edge analytics—has further expanded the scope of Urban AI. These systems enable predictive infrastructure maintenance, proactive responses to environmental hazards, and dynamic emergency routing (Bibri et al., 2024; Jagatheesaperumal et al., 2024). Together, they form what may be described as intelligent urban ecosystems. Yet, as Urban AI systems increasingly automate or mediate decisions with significant social consequences, they raise pressing political and ethical concerns. AI-enabled urban infrastructures can facilitate surveillance, normalize asymmetries of power, and obscure decision-making processes, making issues of legitimacy, transparency, and democratic accountability central rather than peripheral ((Mehan & Dominguez, 2024; Wolniak & Stecuła, 2024).

This article addresses these challenges by conceptualizing Urban AI not as a purely technical innovation but as a governance infrastructure. It advances a framework that distinguishes among cognitive (semantic), data-driven, and hybrid Urban AI models, synthesized from existing research in urban ontologies, urban computing, and hybrid artificial intelligence. These typologies provide a lens for understanding how different AI architecture's structure urban knowledge, decision-making, and accountability. The article is organized into three interconnected parts. First, it develops the theoretical foundations of Urban AI, elaborating the cognitive, data-driven, and hybrid typologies and situating them within the relevant literature. Second, it examines three U.S.-based case studies—AI-enabled emergency vehicle preemption, AI-assisted infrastructure monitoring, and AI-driven traffic signal coordination—to demonstrate how these models operate in practice. Finally, the article critically evaluates the social, environmental, and governance implications of Urban AI, arguing for integrated approaches that balance operational effectiveness with equity, resilience, and democratic legitimacy.

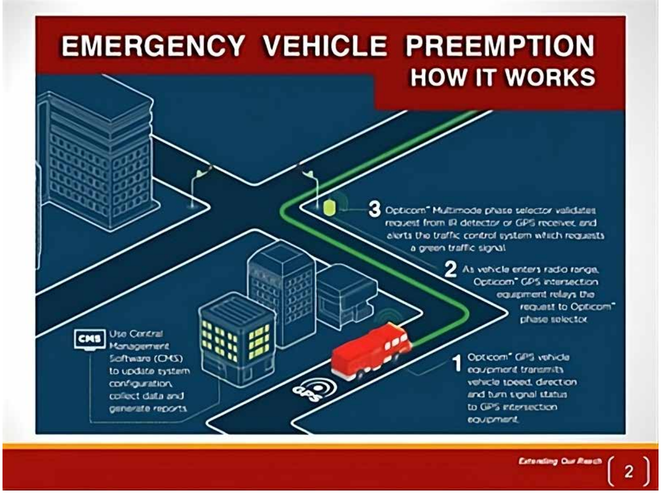
2. Urban AI in Relation to Urban Informatics and Urban Science

Urban Artificial Intelligence builds upon and extends two well-established interdisciplinary traditions: urban informatics and urban science. Situating Urban AI within these fields is essential to clarify its epistemological foundations and to distinguish it from narrower, application-oriented interpretations of artificial intelligence in cities. Urban informatics, as articulated by Foth and colleagues, foregrounds the socio-technical relationships between people, place, and technology, emphasizing participatory processes, situated knowledge, and civic engagement in digitally mediated urban environments (Mehan, 2025a; Foth et al., 2011; Foth et al., 2019). Rather than treating cities as purely computational systems, urban informatics positions digital technologies as embedded within everyday urban life, shaped by social practices, institutional arrangements, and cultural values. From this perspective, Urban AI is not merely a tool for optimization but a mediating infrastructure that influences how urban knowledge is produced, interpreted, and acted upon.

Urban science, by contrast, approaches the city as a complex adaptive system whose dynamics can be analyzed through data-intensive modeling, simulation, and statistical inference (Mehan, 2025b; Batty, 2013; Batty, 2021). Drawing on complexity theory, network science, and spatial analysis, urban science has advanced methods for understanding urban scaling, mobility patterns, land-use change, and infrastructural interdependencies. Urban AI aligns closely with this tradition through its use of machine learning, predictive analytics, and large-scale urban datasets, yet it also extends urban science by enabling adaptive and real-time decision-making rather than retrospective analysis alone.

The conceptual framework advanced in this paper—distinguishing cognitive (semantic), data-driven, and hybrid Urban AI models—emerges at the intersection of these two traditions. Cognitive and semantic approaches resonate with urban informatics by prioritizing interpretability, shared ontologies, and human-centered understanding, while data-driven models reflect the analytical ambitions of urban science (Mehan, 2025c; 2025d; 2025e). Hybrid approaches integrate these logics, combining learning-based optimization with explicit knowledge representations and governance constraints. By grounding Urban AI within urban informatics and urban science, the paper positions artificial intelligence not as a rupture from prior urban scholarship, but as an evolution of long-standing efforts to understand, govern, and co-produce urban systems.

The three lenses—cognitive, data-driven, and hybrid—complement each other and give a more sophisticated picture of what it means to be artificial and intelligent in the urban context. They also provide a better sense of what types of structures, applications, and governance might work within the complicated systems we call cities. The cognitive standpoint underscores the significance of clear semantics and well-structured knowledge in urban environments. Some investigators have crafted ontologies—formal systems that delineate the interconnections among urban entities like road networks, traffic sensors,



EMERGENCY VEHICLE PREEMPTION
HOW IT WORKS

3 Opticom™ Multimode phase selector validates request from IR detector or GPS receiver, and alerts the traffic control system which requests a green traffic signal

2 As vehicle enters radio range, Opticom™ GPS intersection equipment relays the request to Opticom™ phase selector

1 Opticom™ GPS vehicle equipment transmits vehicle speed, direction and turn signal status to GPS intersection equipment

Use Central Management Software (CMS) to update system configuration, collect data and generate reports

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and public transportation routes—to promote interoperability and a shared comprehension of what these systems are and how they function. An effort that stands out is the KM4City framework. This framework takes in different kinds of public and private data, like road conditions and sensor outputs, and reconciles them with the help of semantic models. These services are made available via SPARQL queries to RDF stores (Bellini et al., 2015). In the same way, systematic reviews show that smart-city ontologies improve integration of urban services, enable better handling of big data, and allow for more automated reasoning (Stübinger & Schneider, 2020). These models of being provide a shared conceptual foundation for the coherent communication of different agencies and platforms in an ecosystem of data. They ground Urban AI and, in the process, make possible an ontology of Urban AI.

The data-driven branch concentrates on using large sensor and management datasets to create machine learning models, allowing researchers to sidestep the need for clear semantics in favor of data-driven predictions (Mehan, 2024a; 2024b). Urban computing researchers demonstrate that using deep learning models—like convolutional and recurrent neural networks—can forecast the kinds of patterns and events this fused dataset generates. For instance, they might predict where and when traffic will occur, what kinds of environmental changes are in our near future, or how intense and widespread an emergency response will need to be (Mehan & Casey, 2025; Zou et al., 2024).

Connecting these two approaches, hybrid frameworks embed structured, ontological knowledge within learning-based models. A recent study combined ontological reasoning with machine learning to forecast spring breakups, demonstrating improvements in predictive accuracy and interpretability. Beyond purely hydrological domains, hybrid AI models also surface in (urban) environmental and energy forecasting contexts; for instance, a PSOGA-augmented neural model has been used to predict water demand (Mehan & Mostafavi, 2025; Zubaidi et al., 2024), and deep-learning frameworks have successfully forecasted air quality across urban areas (Aggarwal et al., 2021).

Schematic representation of AI-enabled Emergency Vehicle Preemption (EVP), illustrating how real-time GPS data, predictive arrival modeling, and signal control logic interact to dynamically coordinate green-light corridors for emergency vehicle
Source: Fairfax County EVP system diagram, adapted
Fig. 1

Evaluative literature further illustrates how hybrid strategies enhance city planning. Such approaches typologically include these three: ontological enhancements of machine learning models, semantic data-mining systems, and synergistic reasoning architectures (Ghidalia et al., 2024). Surveys of smart eco-cities serve to complement this portrait. They find that data-driven smart districts are increasingly blending big data techniques with environmental design imperatives. From this survey of the landscape, we can discern a layered architecture for Urban AI. Cognitive, data-driven, and hybrid frameworks form its strata. For the first time in urban history, we have models that obviate the not-so-smart "functional" systems of the past for something more intelligible, adaptable, and ethically grounded. These new systems allow us to say something with confidence regarding Urban AI's capacity to heed the three imperatives of accountability, inclusivity, and resilience.

3. Tools and U.S.-Based Case Studies

This study adopts a purposeful case selection strategy to examine how Urban Artificial Intelligence operates across different infrastructural domains and AI architectures. The three U.S.-based case studies—Fremont (California), New York City, and Seattle—were selected to represent distinct operational contexts (emergency response, infrastructure maintenance, and traffic signal coordination) and to empirically illustrate the three Urban AI typologies developed in the theoretical section: semantic (cognitive), data-driven, and hybrid models. While all cases are drawn from the United States, this deliberate focus allows for comparison within a relatively consistent regulatory and institutional environment; the aim is conceptual generalization rather than statistical representativeness. Together, the cases demonstrate how Urban AI systems are embedded within existing urban governance structures and how different AI architectures shape operational performance, accountability, and equity outcomes.

3.1 Fremont, California – LYT Emergency Vehicle Preemption

The deployment of LYT's AI-driven emergency vehicle preemption system in Fremont, California exemplifies a hybrid Urban AI model, combining real-time data-driven prediction with rule-based traffic control logic.The LYT. emergency platform allows emergency vehicles to converse in real-time with networked traffic signals. This setup allows for a predictive, continuous green-light corridor for emergency vehicles, thanks to cloud orchestration through the Traffic Management Center (GovTech, 2022; Traffic Technology Today, 2022; PR Newswire, 2022). GPS-based vehicle location data and historical traffic patterns are processed in real time to anticipate vehicle arrival at intersections and to coordinate

A retraining NYC A-line subway car, emblematic of the TrackInspect pilot in which Google Pixel smartphones were mounted inside and beneath cars to collect vibration and audio data essential for AI-driven track maintenance (This image reflects the actual rolling stock and setting used in the TrackInspect experiment).
Source: Railway Magazine
Fig. 2

signal preemption accordingly. Empirically, the system produced measurable operational improvements. Fire and ambulance response times were reduced by approximately 18.6% for high-priority calls and up to 69.2% for moderate-priority responses, while average cross-town travel times decreased from 46 minutes to 14 minutes (Traffic Technology Today, 2022). Importantly, these gains were achieved through a software-based intervention, without the installation of new roadside hardware, enabling scalability and cost efficiency.

From a governance perspective, the system incorporates predefined safety rules that allow cross traffic, cyclists, and pedestrians to clear intersections before signal preemption occurs. This design feature links technical optimization to equity and safety considerations, ensuring that emergency prioritization does not disproportionately compromise other road users. Initially deployed across eight intersections as part of Fremont's Vision Zero strategy, the system was later scaled to 37 intersections under a five-year service agreement, illustrating how hybrid Urban AI can be incrementally integrated into existing urban infrastructures.

3.2 New York City – TrackInspect Subway Maintenance Pilot

The TrackInspect pilot, developed by the Metropolitan Transportation Authority (MTA) in partnership with Google Public Sector, illustrates a data-driven Urban AI approach focused on predictive infrastructure maintenance. Over a four-month period (September 2024–January 2025), six Google Pixel smartphones were installed on R46 subway cars operating on the A line. These

A promotional image depicting multiple Seattle intersections and skyline, representing the AI-powered "green wave" emergency routing system deployed by LYT and Yunex across 32 signals near the University of Washington.
Source: Yunex Traffic partnership announcement, 11 July 2023
Fig. 3

devices collected large-scale sensor data, including vibration, audio, and GPS signals—amounting to over 335 million sensor readings and 1,200 hours of audio recordings (MTA & Google Public Sector, 2025; Metro Magazine, 2025). Unlike semantic systems that rely on explicit ontologies, TrackInspect employs machine learning models trained on historical defect data and sensor patterns to identify anomalies associated with track deterioration. Cloud-based processing integrates newly collected sensor data with the MTA's existing defect databases, enabling pattern recognition and probabilistic prediction. The system successfully detected 92% of verified track defects, demonstrating the effectiveness of purely data-driven inference in complex urban infrastructure contexts (Mehan & Mostafavi, 2024; Wired, 2025). The contribution of this system to resilience and equity lies in its preventive orientation. By identifying maintenance needs before failures occur, TrackInspect reduces service disruptions that disproportionately affect transit-dependent populations. Crucially, the system operates as a decision-support tool, augmenting rather than replacing human inspectors, thereby preserving institutional accountability and professional judgment within the maintenance workflow.

3.3. Seattle – AI-Enabled Green Wave Systems for Emergency Routing

Seattle's AI-enabled "green wave" emergency routing system represents a network-level hybrid Urban AI model that integrates real-time data streams with centralized traffic signal coordination. Implemented as part of the MICMA initiative, the system was developed through collaboration between LYT, Yunex Traffic, and the Seattle Department of Transportation (SDOT). It operates across approximately 50 intersections near the University of Washington campus, coordinating emergency vehicle routing through the LYT.speed cloud platform (Yunex Traffic, 2023; SmartCitiesWorld, 2023).

The system integrates live data from the Seattle Fire Department's CAD/AVL dispatch system with SDOT's intelligent transportation infrastructure. Predictive analytics anticipate vehicle trajectories, while rule-based signal logic ensures compliance with safety protocols even when AI controllers are temporarily offline. This hybrid architecture enables both adaptability and robustness—key attributes of resilient Urban AI systems. From an equity and governance standpoint, the system is explicitly designed to optimize signal timing for all road users, not solely emergency vehicles. As noted by SDOT leadership, signal optimization improves safety under varied visibility and traffic conditions, benefiting pedestrians, cyclists, and motorists alike (Seattle DOT, 2024). By shifting from intersection-level preemption to coordinated network governance, the Seattle case illustrates how Urban AI can scale across jurisdictions while maintaining institutional coherence and public accountability.

4. Cross-Case Synthesis

Taken together, these cases demonstrate how different Urban AI typologies operate across urban domains and scales. The Fremont and Seattle systems exemplify hybrid architectures that balance predictive analytics with rule-based governance constraints, while TrackInspect illustrates the strengths and limitations of purely data-driven AI in infrastructure monitoring. Across all cases, claims of resilience, inclusiveness, and equity are grounded not in abstract outcomes but in specific system design choices—including preventive maintenance, safety-oriented signal logic, and human-in-the-loop decision-making.

4.1 Risks, Governance Challenges, and Mitigation Strategies in Urban AI

While Urban Artificial Intelligence offers measurable benefits in domains such as mobility management and emergency response, its increasing integration into urban governance also introduces significant risks that warrant systematic examination. These risks are not merely speculative but emerge from the operational characteristics of AI-driven urban systems, particularly their reliance on large-scale data collection, automated decision-making, and opaque optimization processes.

One major risk concern algorithmic opacity and accountability. Many Urban AI systems—especially data-driven and learning-based models—operate as black boxes, making it difficult for public agencies and citizens to understand how decisions are made or to contest erroneous outcomes (Wolniak & Stecuła, 2024). This lack of interpretability can undermine democratic oversight, particularly in safety-critical contexts such as emergency routing and infrastructure prioritization.

A second risk relates to equity and spatial justice. Urban AI systems trained on historical data may reproduce or amplify existing spatial inequalities, directing resources toward already well-served areas while marginalizing others. In mobility and emergency response systems, this can translate into uneven service provision and differential exposure to risk (Bibri, 2021). Without deliberate corrective mechanisms, efficiency-oriented optimization may conflict with social equity goals. A third concern involves surveillance and data governance. AI-enabled urban infrastructures often depend on continuous sensing, location tracking, and behavioral data, raising issues of privacy, consent, and function creep (Mehan, 2023a; 2023b). When integrated across platforms, these systems can enable forms of pervasive monitoring that exceed their original operational purpose. To address these risks, the literature increasingly emphasizes governance-oriented mitigation strategies. These include embedding human-in-the-loop decision-making, defining explicit normative constraints within optimization objectives, adopting transparency and auditability standards, and ensuring participatory oversight in system design and deployment. In the context of Urban AI, mitigation should be understood not as a technical add-on but as a core design requirement aligned with public values and institutional accountability. By situating risks and responses within the operational realities demonstrated by the case studies, this analysis underscores that the societal impact of Urban AI depends less on the technology itself than on the governance frameworks through which it is implemented.

4.2 Academic Models: Reinforcement Learning and Operational Optimization

This section complements the preceding empirical case studies by examining academic Urban AI models that have not yet been widely deployed at scale but play a critical role in shaping the future of urban governance and infrastructure optimization. Unlike the applied cases discussed earlier, these models are primarily developed and tested in research settings and simulation environments. Their inclusion serves two purposes: first, to illustrate how Urban AI is being theorized and operationalized in the academic literature beyond commercial platforms; and second, to demonstrate how advanced learning-based models extend the conceptual typologies of Urban AI—particularly data-driven and hybrid approaches—toward more adaptive, anticipatory, and system-level decision-making.

4.3 Reinforcement Learning for Network-Level Urban Optimization

Reinforcement learning (RL) is a class of machine learning methods in which an agent learns to make sequential decisions by interacting with an environment and optimizing long-term rewards rather than immediate outcomes. RL is particularly well suited to dynamic, uncertain, and multi-agent urban systems, such as traffic networks, where conditions change continuously and decisions at one location affect outcomes elsewhere. For this reason, RL has become increasingly prominent in urban mobility research, signal control, and emergency routing.

The EMVLight framework exemplifies this approach. EMVLight is a multi-agent deep reinforcement learning model in which each traffic intersection functions as a learning agent that cooperatively optimizes emergency vehicle routing and signal control across a network (Su et al., 2022; Su et al., 2023). Unlike traditional shortest-path algorithms, which focus solely on minimizing travel time for a single vehicle, EMVLight simultaneously considers emergency and non-emergency traffic, optimizing overall network performance. Simulation results demonstrate substantial reductions in emergency response times (42.6%) while also improving travel efficiency for non-emergency vehicles (23.5%). Within the Urban AI framework developed in this article, EMVLight represents a data-driven model with hybrid governance implications. While the learning process is largely data-driven, the model's reward structure embeds normative priorities—such as minimizing disruption to non-emergency traffic—thereby illustrating how ethical and equity considerations can be indirectly encoded into optimization objectives. This makes reinforcement learning a powerful, but governance-sensitive, tool for future Urban AI systems.

4.4 CNN-Based Predictive Models and Operational Resource Allocation

The inclusion of convolutional neural network (CNN)-based models follows reinforcement learning because both approaches address operational optimization, albeit at different stages of decision-making. While reinforcement learning focuses on real-time control and coordination, CNN-based models are commonly used for predictive optimization, particularly in forecasting spatial and temporal demand patterns.

In urban emergency services, CNN-based models have been applied to predict future emergency call volumes by transforming time-series data into spatial heatmaps that incorporate contextual variables such as weather, public events, and holidays (Rautenstrauß et al., 2023). These predictions enable proactive ambulance positioning and resource allocation, improving system-wide responsiveness before emergencies occur. In empirical evaluations using Seattle's 911 call data, CNN-based models outperformed traditional forecasting techniques by more than 9% in prediction accuracy.

From the perspective of Urban AI typologies, CNN-based forecasting represents a purely data-driven approach, relying on pattern recognition rather than explicit semantic representations of urban systems. Its contribution to operational optimization lies in improving anticipatory governance—allowing urban agencies to allocate resources more equitably and efficiently across space and time. When combined with downstream control systems, such as reinforcement learning–based dispatch or routing, predictive models become a critical component of integrated Urban AI ecosystems.

These academic models are presented here not as isolated technical achievements but as conceptual building blocks for future Urban AI deployments (Mostafavi & Mehan, 2024). Their focus on transportation and emergency response reflects the maturity of data availability and the high societal stakes of these domains, where optimization outcomes are measurable and governance implications are immediate. Together, reinforcement learning and CNN-based forecasting illustrate how Urban AI is evolving toward system-level, learning-based governance infrastructures that can balance efficiency, resilience, and equity—provided that their objectives, constraints, and accountability mechanisms are carefully designed.

5. Conclusion

The three case studies examined in this article—Fremont's AI-enabled emergency vehicle preemption, New York City's AI-assisted subway maintenance, and Seattle's AI-driven green wave signal coordination—together demonstrate how Urban Artificial Intelligence is reshaping urban governance through incremental, operational interventions rather than large-scale infrastructural overhaul. Across these contexts, Urban AI functions less as a speculative future technology and more as a pragmatic governance tool embedded within existing institutional systems. Its transformative capacity lies in improving how cities respond to emergencies, maintain critical infrastructure, and manage mobility in ways that are visible, measurable, and socially consequential.

Taken together, these cases illustrate a continuum of Urban AI maturity, ranging from targeted software-based optimizations to more integrated, network-level coordination systems. Importantly, the benefits observed—reduced response times, improved safety, preventive maintenance, and system-wide efficiency—are not produced by technological sophistication alone. Rather, they emerge from specific design choices, including human-in-the-loop decision-making, rule-based safety constraints, and anticipatory rather than reactive governance. These features ground claims of resilience and inclusiveness in concrete operational mechanisms rather than abstract aspirations. At the same time, the cases underscore that Urban AI does not inherently resolve questions of equity, transparency, or democratic legitimacy. As demonstrated throughout the paper, AI systems can just as easily reinforce existing governance logics if their objectives, constraints, and accountability structures remain unexamined. The findings therefore support a cautious but constructive position: Urban AI should be understood as a governance infrastructure, whose societal impact depends on how learning objectives are defined, how decisions remain interpretable, and how institutional responsibility is maintained. Rather than advancing dystopian or speculative claims, this article argues for a grounded approach to Urban AI, one that evaluates systems through their real-world performance, governance arrangements, and distributive effects. When aligned with clear public priorities, environmental responsibility, and participatory oversight, Urban AI can contribute meaningfully to safer, more resilient, and more equitable urban systems. Its promise lies not in replacing human judgment, but in augmenting urban decision-making in ways that remain accountable to democratic values and the lived realities of city residents.

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