Journal of

Organisational Studies and Innovation

Vol. 12, no.4, Winter 2025

Risk Governance in Resilient Cities and Artificial Intelligence: A New Political Stakeholder?

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Abstract: Cities face increasingly complex risks, from climate extremes to pandemics, while deploying artificial intelligence (AI) across urban operations. This article asks whether AI should be treated as a non-human stakeholder in urban risk governance. Integrating risk governance, anticipatory governance, and Actor–Network Theory, we conduct a comparative qualitative analysis of three city cases: Calgary (climate resilience and infrastructure planning), Copenhagen (public-building energy management), and Kansas City (AI-enhanced mobility). Across cases, AI systems shape problem framing, prioritize interventions, and execute micro-decisions in real time, shifting from instruments to delegates and, at times, co-governors. We propose an AI-as-actor spectrum anchored to core risk-governance tasks and derive indicators of "effective agency" (e.g., automated problem framing, resource-allocation authority, auditability/contestability). Findings show that AI's influence scales with how early models enter the governance cycle, how tightly outputs are coupled to execution, and how contestable algorithmic "passage points" are. Policy implications include public algorithm registers, ex ante impact assessments, human-in-the-loop thresholds with escalation rights, decision logging, and periodic audits to safeguard transparency, accountability, and equity. Reconceptualizing governance to include non-human actants does not confer personhood on AI; it clarifies its embedded role and the institutional tools needed to govern it.

Keywords: *Artificial Intelligence (AI), Resilient City, Actor-Network Theory, Risk Governance, Anticipatory Governance, Smart Cities.*

Introduction

Cities face increasingly systemic and rapidly changing risks from climate extremes and cascading infrastructure failures, as well as public health shocks, while also adopting artificial intelligence (AI) across urban operations, planning, and service delivery. In practice, AI now helps classify problems, prioritize interventions, and allocate scarce resources in real time (e.g.,

[1] https://doi.org/10.51659/josi.25.268

mobility optimization, energy balancing, flood early warning). This creates a key challenge for resilience and risk governance: when, how, and to what extent does AI operate not only as a tool but as an actor that influences governance choices and outcomes? Recent policy work highlights both the widespread adoption of AI and the governance stakes involving transparency, accountability, and inclusion in public decision-making. (OECD, 2025; UN-Habitat, 2024).

Risk governance frameworks emphasize proactive, multi-actor coordination in the face of uncertainty, with a focus on interdependencies and systemic impacts. Recent insights from the International Risk Governance Council (IRGC) and related research highlight how new technologies can transform risk creation, detection, and management within socio-technical systems—precisely where resilient cities focus their efforts. Including AI in this context adds complexity to the distribution of agency, as the design of models, data pipelines, and algorithmic capabilities can shape how risks are conceptualized and which options are deemed feasible or legitimate. (IRGC, 2023; IRGC, 2025; Mehryar et al., 2024).

Actor–Network Theory (ANT) provides a vocabulary for analyzing such configurations by treating agency as distributed across human and non-human actants. Recent work in public administration and political science invites us to revisit AI's role beyond "tool" metaphors and to examine how algorithms co-produce governance through the classification at scale, the delegation of discretion, and the routinization of discretion. This implies that AI systems can shape attention, sequence actions, and rewire accountability chains—even when humans remain "in" or "on" the loop (Alon-Barkat & Busuioc, 2024; Başkan, 2024; Criado et al., 2025; Farrell, 2025; Gurumoorthi & Meiller, 2024).

Yet we still lack a clear integration of ANT's insights with risk governance in resilient city contexts. Prior studies typically treat "AI in government" through adoption or ethics lenses, while ANT-inspired analyses rarely operationalize consequences for risk assessment, option generation, and decision rights across urban resilience functions. This paper addresses that gap through a comparative analysis of three city cases (Calgary, Copenhagen, and Kansas City) where AI is embedded in critical urban systems relevant to resilience. We conceptualize AI as a semi-autonomous stakeholder whose effective agency varies with data infrastructures, delegation arrangements, and oversight regimes, and we examine how that variation affects risk governance capacities in practice.

We aim to theorize and empirically illustrate how AI reshapes risk governance in resilient cities by acting as an organizationally embedded, semi-autonomous stakeholder rather than a mere instrument. For this purpose, the following questions constitute the research agenda of this paper:

> RQ1: Under what conditions do city-deployed AI systems exhibit agency-like effects in risk governance (problem framing, prioritization, and allocation)?
>
> RQ2: How does AI's embedding in socio-technical networks redistribute discretion, responsibility, and accountability among human and non-human actors?
>
> RQ3: What are the implications of such redistributions for core resilience functions (anticipation, preparedness, response, and learning)?

Building on our research aim and questions, we make three interrelated contributions to the study of AI's role in urban risk governance. First, we synthesize risk governance (IRGC-informed) and ANT to offer an AI-as-actor spectrum—from instrument → delegate → co-governor—anchored to specific risk governance tasks (scoping, appraisal, option space curation, and decision execution). Second, we derive operational indicators of AI's effective agency (e.g., degree of automated problem framing, resource allocation authority, and auditability/contestability) to enable comparison across cities and sectors. Third, through three comparative cases, we identify governance design levers—such as transparency instruments, escalation protocols, and human-in-the-loop thresholds—that can harness AI's benefits for resilience while preserving accountability and equity. Collectively, these contributions advance ANT-based interpretations of technology in governance by specifying mechanisms and measurement points that matter for risk governance outcomes in resilient cities (IRGC, 2025; OECD, 2025).

Methodology

This study employs a qualitative, exploratory research design to investigate the evolving role of AI in governing urban resilience. Given the complexity and emerging nature of the subject matter, a comparative case study methodology was chosen to capture variation across multiple city-level applications of AI in different governance contexts (Flyvbjerg, 2006, p. 221; Yin, 2014, p. 56). This approach enables a contextualized, multidimensional understanding of how AI technologies interact with urban systems and stakeholders in risk management.

Situating the Methodological Framework: Qualitative Secondary Analysis (QSA)

The empirical foundation of this study is Qualitative Secondary Analysis (QSA), a methodological approach that is increasingly recognized. QSA is defined as the reuse of existing data, originally gathered for another purpose, to investigate a new research question (Tate & Happ, 2018). Given this article's novel theoretical lens, which conceptualizes AI as a socio-technical actor within urban risk governance networks, QSA is not merely a matter of convenience but a deliberate and strategic methodological choice.

The focus of this study is not on the subjective experiences or perceptions of individual actors regarding AI, but rather on how AI becomes embedded within, and subsequently reconfigures, institutional governance architectures. For investigating such macro-level systemic dynamics, the richest and most direct empirical sources are the textual artifacts these systems produce to define, legitimize, and enact themselves. Data sources such as policy documents, planning reports, technical specifications, and institutional websites do not merely provide information about governance systems; they are, in fact, primary manifestations of these systems. Consequently, a strong ontological alignment exists between the object of inquiry—the institutional discourse and the socio-technical network itself—and the selected data type: the texts that document this very discourse and network. Beyond its practical advantages, such as cost-effectiveness and efficiency, this approach offers access to institutional-scale data that would be difficult, if not impossible, to capture through individual interviews (Irwin, 2013; Ruggiano & Perry, 2019; Tate & Happ, 2018).

Data Sources and Enhancing Credibility: A Triangulation Strategy

To mitigate the potential weaknesses of relying on a single data type, this study employs a rigorous data source triangulation strategy. Triangulation is a research strategy that enhances the validity and credibility of findings by leveraging multiple data sources, methods, or investigators to examine the same phenomenon. This approach aims to mitigate the biases inherent in any single source, thereby enabling the construction of a more holistic, nuanced, and robust analysis.

During the data collection process, a diverse range of secondary sources were systematically compiled for each case study (Calgary, Copenhagen, and Kansas City), organized into the following categories:

- **Official Institutional Sources**: Policy documents, urban planning reports, and official websites published by municipal governments and related public agencies. These sources provided the formal, sanctioned narrative regarding the purpose and function of the AI systems.
- **Technical and Evaluative Sources**: Project evaluations, technical reports (white papers), and academic publications. These documents offered deeper insight into the technology's operational logic, design assumptions, and reported outcomes.

- **Public and Media Sources**: News reports from reputable media outlets and professional interviews available in public archives. These sources yielded valuable data on public perception, potential controversies, and critical external perspectives.

Analyzing these diverse sources in conjunction served to counterbalance the inherent biases of any single one. For instance, the tension between the laudatory narrative in a municipality's promotional policy document and the critical perspective in a media report created an analytically productive space. Such discrepancies were treated not merely as a data problem, but as an indicator of a political or institutional terrain of contestation that warranted investigation. This systematic comparison significantly enhanced the credibility of the findings.

Case Selection Criteria and Corpus

Four main criteria guided the selection of cases:

1. Functional diversity: The cases were chosen to represent various aspects of urban resilience, specifically climate adaptation and infrastructure planning (Calgary), energy management (Copenhagen), and smart mobility (Kansas City). This approach facilitates cross-sectoral insights into AI applications.

2. Geographic and socio-political variation: Cities represent diverse governance regimes and regional contexts (North America and Europe), thereby broadening the range of institutional and technological variation in the analysis.

3. Evidence of AI integration: Only cities where AI technologies were visibly integrated into urban governance processes, beyond isolated pilot projects, were included. Each case involved AI systems used for decision-making, resource allocation, or real-time urban management.

4. Data accessibility: Preference was given to cases with publicly available documentation, including policy reports, project evaluations, academic literature, and credible media sources.

These criteria were used to ensure conceptual richness, comparative potential, and analytical feasibility, resulting in the selection of Calgary, Copenhagen, and Kansas City as focal cases. Our documentary corpus spans strategy documents, council minutes, tender/specification files, vendor manuals, audits, and regulator briefs for Calgary, Copenhagen, and Kansas City (2016–2025). Where available, we included multiple editions of the same instrument (e.g., revised strategies, updated specifications) to track changes in governance arrangements and AI capabilities over time. This multi-source approach allows for triangulation and enhances the credibility of the analysis (Bowen, 2009, p. 28).

Analytical Framework

The analysis is informed by the theoretical perspectives of risk governance (Renn, 2017), anticipatory governance (Guston, 2010; Lehoux et al., 2020), and Actor-Network Theory (Latour, 2005), which collectively frame AI as a potentially active, semi-autonomous stakeholder in urban governance systems. To transparently delineate the logical flow of this research, an analytical framework was developed to demonstrate how theoretical concepts were operationalized into concrete empirical indicators. APPENDIX Table **1** below illustrates this systematic pathway, mapping the process from the initial research questions to the final data analysis. This table serves not only as a tool to guide the analysis but also underscores that the research is not an indeterminate exploratory exercise. Instead, it demonstrates that this is a structured inquiry, grounded in theory and guided by explicitly operationalized criteria.

Limitations

While the comparative case study method affords rich contextual insights, this study is subject to certain limitations. A frank discussion of these limitations is essential, both for delineating the boundaries of the study's claims and for ensuring that the findings are transparently situated within broader scholarly discourse. Qualitative research is an inherently interpretive endeavor. The findings are inevitably shaped by the researcher's theoretical lenses and analytical choices. In this study, several disciplinary mechanisms were employed to mitigate researcher bias, particularly confirmation bias. These included the structured analytical framework detailed above (see Table 1) and a hybrid coding process. That said, the findings are generated through the specific theoretical frameworks of Actor-Network Theory and Risk Governance. It is an inherent and accepted feature of interpretive social science that a different theoretical approach might yield different interpretations from the same dataset. As such, rather than laying claim to a definitive 'truth,' this study offers an interpretation that is empirically grounded, methodologically transparent, and informed by its chosen theoretical perspective.

Risk Governance Framework in Resilient Cities

The concept of urban resilience has gained increasing traction across public policy, disaster risk management, and urban planning. Defined broadly as the capacity of urban systems to absorb, adapt to, and recover from shocks and stresses while maintaining essential functions, resilience constitutes a foundational element of sustainable urban development (Figueiredo, Honiden, & Schumann, 2018; Meerow et al., 2016). As cities face intensifying challenges from climate-induced hazards to pandemics and cascading socio-economic disruptions, the governance of risk has emerged as a critical area of inquiry and practice.

The OECD identifies four interdependent pillars that underpin the development of resilient cities: economic, social, environmental, and governance dimensions (Figueiredo, Honiden, & Schumann, 2018, pp. 17-19). These dimensions form a holistic framework through which resilience is operationalized across urban systems:

- *Economic resilience* refers to a local economy's ability to withstand and recover from shocks while maintaining employment, investment, and productivity. It includes mechanisms for fiscal risk management, economic diversification, and continuity planning (Martin & Sunley, 2015, pp. 2-3).
- *Social resilience* refers to a community's ability to cope with adverse events through cohesion, adaptability, and trust in its institutions. It is closely tied to equity, social capital, and access to essential services (Adger, 2000, pp. 347-348).
- *Environmental resilience* refers to the capacity of urban ecosystems and infrastructure to withstand environmental disturbances, adapt to changing conditions, and maintain their ecological functionality. This includes sustainable land use, climate adaptation strategies, and nature-based solutions (UNDRR, 2019, pp. 316-319).
- *Governance*, the most integrative pillar, concerns the institutions, actors, and processes that enable coordinated, inclusive, and anticipatory decision-making. Governance not only mediates how risks are framed and addressed but also determines whose voices are included in defining resilience priorities (Baud & Hordijk, 2009, pp. 7-8).

Within this framework, risk governance has become an increasingly salient paradigm. Unlike traditional risk management, which often focuses on technical fixes and isolated interventions, risk governance emphasizes participatory, systemic, and adaptive approaches (IRGC, 2017; Renn, 2017). It addresses the complexity and uncertainty of modern risks by involving a broad spectrum of stakeholders and by embedding risk processes into democratic governance structures.

One of the most comprehensive articulations of risk governance is found in the International Risk Governance Council (IRGC) Framework, which advocates for a multi-phase process: pre-assessment, risk appraisal, characterization and evaluation, risk management, and risk communication. Central to this model is the integration of expert knowledge with stakeholder perspectives to foster legitimacy, credibility, and trust in governance systems (IRGC, 2017, pp. 5-6).

In the context of urban resilience, several practical instruments embody the risk governance approach (Figueiredo, Honiden, & Schumann, 2018: 17; UNDRR, 2019, p. 54):

- Emergency response plans facilitate preparedness and institutional coordination during crises.
- Early-warning systems, increasingly supported by digital technologies, enable the anticipation of emergent threats.
- Stakeholder engagement mechanisms that promote inclusivity, transparency, and co-production of knowledge.

However, the intensifying complexity and interconnectivity of urban risks necessitate new models of governance, ones that are anticipatory, data-driven, and technologically enhanced. As cities increasingly rely on real-time data, predictive analytics, and algorithmic decision-making, emerging technologies such as AI are no longer peripheral tools but integral components of governance processes. This development raises a fundamental question: can AI be conceptualized as a tool and a *stakeholder* in urban risk governance?

The following section examines this proposition by situating AI within contemporary risk governance practices and exploring its potential to shape resilient, intelligent urban futures.

Artificial Intelligence and Risk Governance in Resilient Cities

In an age defined by complexity, uncertainty, and interdependence, cities are increasingly called upon to anticipate, mitigate, and adapt to a wide array of risks-from climate-related disasters to cyber threats and public health emergencies. The notion of resilience has thus emerged as a central paradigm in urban governance, emphasizing not only the physical robustness of infrastructure but also the institutional, social, and technological capacities of cities to manage disruption (Meerow et al., 2016, pp. 39-40; UNDRR, 2019, p. 54).

Among the most transformative developments in this regard is the integration of AI into urban risk governance. Traditionally associated with the "smart city" discourse, AI is now being reframed as a vital tool-and potentially even a governance actor-in shaping the resilience of urban systems (Kitchin, 2014, pp. 3-4; Batty et al., 2012, p. 483).

While the smart city paradigm emphasizes data-driven efficiency and optimization, the resilient city framework is more expansive, focusing on robustness, redundancy, and adaptability in the face of disruption (Vale, 2014, p. 191). AI technologies, when embedded into urban systems, support what scholars describe as anticipatory governance-a form of governance that emphasizes proactive, forward-looking decision-making based on continuous risk detection and adaptive response mechanisms (Guston, 2010, p. 434; Quay, 2010, p. 498). These technologies have the potential to equip urban actors to respond to risks before they materialize, making cities more agile and responsive in uncertain environments (Lehoux et al., 2020, pp. 12-13).

These capabilities are particularly relevant to risk governance, as defined by Renn (2008: 10) as the institutionalized processes of identifying, evaluating, managing, and communicating risks in ways that are inclusive, transparent, and adaptive. Unlike conventional risk management approaches, risk governance embraces uncertainty, involves diverse stakeholders, and addresses the socio-political dimensions of risk, thereby demanding not only technical expertise but also deliberative democratic mechanisms.

AI applications are currently being used across multiple stages of the risk governance cycle. In the risk assessment phase, machine learning algorithms analyze vast and heterogeneous data sources, including climate data, urban mobility patterns, and social media activity, to detect anomalies and assess vulnerability (Hohma et al., 2023, p. 4; Taeilhagh, 2021, pp. 140-141). For example, in India, real-time flood prediction systems powered by AI integrate rainfall, terrain, and infrastructure data to produce highly accurate forecasts, enabling preemptive evacuations and optimized resource allocation (PIB, 2022).

In the risk management phase, AI supports decision-making by simulating complex scenarios, modeling cascading impacts, and optimizing logistics. As Taddeo and Floridi (2018, pp. 751-752) highlight, while AI has demonstrated high efficacy in fields such as medical diagnostics and cybersecurity, reducing diagnostic errors in breast cancer by 85% and shortening cyberattack detection time from over 100 days to mere hours, these capacities also inform urban resilience strategies, particularly in domains like public health surveillance and cyber risk response planning. Reinforcement learning models have also been employed to design emergency evacuation routes in densely populated urban areas (Jin et al., 2025, p. 4).

Furthermore, AI supports risk communication by converting complex data into clear visualizations and offering real-time updates for decision-makers and the public. Natural Language Processing (NLP) systems can synthesize emergency bulletins or translate early warning signals into accessible, actionable formats (UNDRR, 2020), ensuring that crucial information reaches citizens efficiently during crises.

In the realm of risk communication, AI applications are rapidly expanding. Beyond static data dashboards, cities such as Tokyo and Taipei have deployed AI-powered chatbots that can deliver real-time emergency alerts, safety instructions, and evacuation routes through familiar messaging platforms. These systems often include multilingual functionality, enhancing accessibility for immigrant and tourist populations (Tokyo Metropolitan Government, 2020). Moreover, emerging “emotion-aware” AI models can interpret public sentiment on social media during crises, enabling authorities to adapt their messaging strategies in real-time (Liu et al., 2023, p. 3519). These developments show that AI does not merely transmit risk information; it can mediate, personalize, and adapt communication based on evolving urban conditions and community feedback. These multifaceted applications demonstrate that AI is not only a technological tool but also an increasingly strategic instrument that shapes and is shaped by urban governance priorities.

Building on Actor-Network Theory (ANT) (Latour, 2005, pp. 72-73), some scholars propose that technologies such as AI, due to their operational autonomy, embeddedness in decision-making infrastructures, and impact on human behavior, exercise agency within sociotechnical systems. This challenges traditional political theory, which often reserves stakeholder status for actors possessing intentionality, moral responsibility, and representational capacity. Yet, in practice, AI systems are increasingly making consequential decisions, influencing policy outcomes, and interacting with human actors in ways that blur the boundaries between instrumentality and agency (Coeckelbergh, 2020, p. 125).

This ontological shift invites several critical questions:

- Should AI systems be subject to political accountability?
- Can they be meaningfully included in participatory governance processes?
- What institutional and legal mechanisms are required to regulate their influence in ways that align with democratic values?

While definitive answers to these questions remain elusive, their emergence highlights the inherently political nature of AI in urban governance. They also emphasize the need for a reflexive, inclusive, and adaptive model of technology governance, one that balances innovation with oversight and efficiency with equity.

AI holds immense promise for enhancing the resilience of urban systems through improved foresight, responsiveness, and evidence-based decision-making. Yet its integration into risk governance frameworks also introduces normative, ethical, and institutional dilemmas that cannot be resolved solely through technical fixes. As cities become increasingly dependent on AI-enabled systems, their governance models must evolve to ensure transparency, fairness, and inclusivity not only in policy outcomes but also in the processes that produce them.

Despite these advances, AI's growing role in urban governance raises significant epistemological and ethical concerns. One of the most debated issues is the “black box” nature of many AI systems (particularly those based on deep learning), which makes it difficult to interpret how decisions are reached. As Burrell (2016) explains, opacity may arise from technical complexity, proprietary code, or even institutional reluctance to disclose algorithmic logic. In the context of urban risk governance, such opacity can erode transparency, public trust, and political accountability, mainly when AI-driven decisions affect public safety or resource allocation. Cities must therefore consider developing explainable AI (XAI) frameworks to ensure that AI systems align with democratic values and are subject to meaningful oversight and scrutiny.

The following section examines how various cities have addressed this challenge through concrete applications of AI in risk governance, offering a comparative perspective on best practices, institutional innovations, and potential pitfalls.

Findings and Discussion

To investigate the evolving role of artificial intelligence (AI) as a stakeholder in urban risk governance, this section presents a comparative analysis of three international city-level case studies. These cases were selected to reflect a diversity of contexts, risk types, and governance innovations where AI technologies have been integrated into resilience-building strategies. Each case offers insights into how AI extends its capabilities beyond its technical limitations, potentially adopting a more integrated, participatory, and influential role in shaping urban responses to complex risks.

Case 1: Calgary, Canada – AI for Climate Resilience and Infrastructure Planning

The city of Calgary launched the "AI for the Resilient City" initiative to integrate machine learning into climate risk mapping, infrastructure development, and the enhancement of blue-green networks. This platform synthesizes geospatial data, environmental risk indicators, and community input to inform public infrastructure investments (Evergreen, 2023). As a result, the city has enhanced its decision-making capacity in planning resilient neighborhoods, particularly those vulnerable to the impacts of climate change. The initiative demonstrates how AI contributes not only to technical analysis but also to participatory planning by including diverse datasets and local needs.

Case 2: Copenhagen, Denmark – AI in Public Building Energy Management

Copenhagen has applied AI technologies to monitor and optimize energy consumption in public buildings. The system adjusts heating and electricity usage in real time based on internal and external environmental data (Pictet Asset Management, 2024). This initiative aligns with the city's broader climate neutrality goals and reflects a systemic effort to embed sustainability into urban infrastructure. By enabling energy savings and reducing carbon emissions, the system supports both environmental resilience and efficient public sector governance.

Case 3: Kansas City, United States – AI-Enhanced Traffic and Mobility Management

In Kansas City, AI processes real-time traffic data from IoT sensors and dynamically adjusts traffic signals. This smart mobility infrastructure has reduced congestion and improved travel efficiency in key corridors, reportedly shortening commute times by up to 25% (Viridis Initiative, 2023). The application illustrates how AI can act as a responsive agent within urban systems, influencing both infrastructure performance and resident well-being.

Cross-Case Analysis

Across Calgary, Copenhagen, and Kansas City, three common patterns emerge that clarify when AI moves from “instrument” toward “delegate” or even “co-governor” within urban risk governance. First, in all three settings, AI participates in problem framing by curating what counts as salient risk signals in real time (e.g., climate hazards, building energy demand, or congestion patterns), thereby shaping which interventions are viewed as feasible or urgent (Evergreen, 2023; Pictet Asset Management, 2024; Viridis Initiative, 2023). Second, AI influences prioritization and allocation by ordering options (e.g., where to invest in blue-green infrastructure, when to pre-heat buildings, which corridors receive green waves), which gives computational models a de facto agenda-setting role. Third, each system is embedded in organizational routines (planning, facilities management, traffic control) that institutionalize algorithmic recommendations—an embedding that is decisive for whether AI functions merely as a tool or attains stakeholder-like influence consistent with ANT’s account of distributed agency (Latour, 2005) and with anticipatory governance’s emphasis on foresight, monitoring, and adaptive feedback (Guston, 2010; Quay, 2010).

Similarities are most substantial in the delegation of micro-decisions under time pressure and uncertainty: Copenhagen's building controls, Kansas City's signal timing, and Calgary's spatial risk stratification all automate parts of appraisal and execution loops that humans historically performed. Yet contextual differences matter for the magnitude of AI's "effective agency." Calgary's planning suite acts earlier in the governance cycle (scoping/appraisal) and affects capital allocation over longer horizons; Copenhagen's controls operate continuously within facilities management; Kansas City's stack focuses on second-by-second operations. These temporalities co-determine the stakes: longer-horizon systems (Calgary) shape distributive outcomes across neighborhoods, while real-time systems (Copenhagen, Kansas City) shape service quality and safety on a day-to-day basis. Oversight also varies: Calgary relies on planning instruments and deliberative review; Copenhagen is oriented to performance targets (emissions, costs); Kansas City emphasizes operational service levels and incident response. In ANT terms, each case constructs different "obligatory passage points" that humans must navigate to contest or override algorithmic choices—such as planning hearings in Calgary, building management consoles in Copenhagen, and traffic operations centers in Kansas City. In terms of anticipatory governance, the cases differ in how systematically they close the loop between model forecasts, public values, and learning (IRGC, 2017; OECD, 2024).

Read through the lens of the paper's AI-as-actor spectrum, Calgary sits at the delegate → co-governor boundary when model outputs are routinized into capital programming; Copenhagen is a high-delegation environment with bounded discretion and clear performance envelopes; Kansas City delegates time-critical coordination while retaining human escalation, aligning with "human-on-the-loop" practices. These contrasts help explain cross-case variation in discretion, accountability chains, and the scope for public contestation—core concerns in risk governance (Renn, 2017) and anticipatory governance.

Across all cases, AI acts not merely as a tool but as an embedded element within the city’s governance architecture, influencing decisions, shaping priorities, and interacting with human and institutional actors.

From Instrument to Actor: Artificial Intelligence as a Non-Human Stakeholder in Urban Governance

The integration of AI into urban risk governance signals a shift in how public decisions are framed, prioritized, and executed. Beyond functioning as a mere instrument, AI increasingly participates in sense-making and coordination, raising the question of when it should be treated as a stakeholder within governance systems (Latour, 2005; Guston, 2010).

Calgary (Climate resilience & infrastructure planning): With machine-learning layers synthesizing geospatial hazards and community inputs, AI co-frames the risk landscape and curates option spaces (RQ1). Because spatial prioritizations flow into budgetary and design choices, discretion shifts from planners acting ex post to model-conditioned choices ex ante—an ANT-style redistribution of agency via inscription and translation (RQ2). Governance implications include the need for transparent criteria, audit trails, and participatory review when algorithmic maps become "decision substrates," consistent with anticipatory governance's emphasis on foresight coupled to deliberation (RQ3) (Evergreen, 2023; Latour, 2005; Guston, 2010; IRGC, 2017).

Copenhagen (Public-building energy management): Here, AI forecasts demand and executes set-point adjustments, embedding predictive control within facilities' routines (RQ1). Discretion migrates from individual operators to system-level policies and vendor-defined control logic, creating a clear "obligatory passage point" in the building management system (RQ2). Anticipatory governance benefits (emissions and cost risk hedging) are balanced by requirements for explainability, override protocols, and periodic model validation to maintain accountability and align with public mandates (RQ3) (Pictet Asset Management, 2024; Renn, 2017; OECD, 2024).

Kansas City (AI-enhanced mobility): Real-time optimization turns sensor streams into signal plans, reframing congestion as a continuously managed risk (RQ1). Discretion shifts toward the algorithm during peak load, with human operators retaining escalation rights—an instance of distributed agency that ANT predicts when non-human actants stabilize routines (RQ2). Anticipatory gains (incident mitigation, safety) require traceable decision logs, fairness tests across corridors, and public-facing performance dashboards to preserve legitimacy (RQ3) (Viridis Initiative, 2023; Latour, 2005; IRGC, 2017; OECD, 2024).

The three case studies highlight the diverse and expanding roles of AI within resilient urban systems. While Calgary focuses on climate resilience and community-based planning, Copenhagen addresses energy optimization and environmental sustainability. Kansas City emphasizes real-time operational efficiency through AI-enhanced mobility systems. The comparative dimensions are summarized in Table 2 below.

Bridging forward, these cross-case results indicate that AI's "effective agency" scales with (a) how early in the governance cycle models enter, (b) how tightly outputs are coupled to execution, and (c) how contestable the algorithmic passage points are. Designing transparency instruments, escalation rights, and participatory review at those passage points operationalizes ANT's insight about enrollment and translation while meeting the demand for foresight with accountability in anticipatory governance (Latour, 2005; Guston, 2010; OECD, 2024; IRGC, 2017).

Beyond Instrumentality: Conceptualizing AI as an Actor

In the conventional division of labor between humans and technologies, machines serve as instruments, extensions of human intention and control. Yet recent literature challenges this view. Actor-Network Theory (ANT), particularly as developed by Latour (2005), suggests that technologies possess "actancy": the capacity to make a difference in a network of relations. While AI lacks consciousness or intentionality, it nonetheless exerts causal influence, not only interpreting risks but structuring how they are prioritized, communicated, and acted upon.

As Coeckelbergh (2020) argues, AI systems today are integral to decision architectures that directly influence public policy, urban mobility, energy allocation, and climate resilience. These are not trivial domains. In our case studies, for example, Calgary's AI platform influenced which neighborhoods were prioritized for green infrastructure; Copenhagen's AI system determined heating levels in public buildings; and Kansas City's traffic AI altered real-time mobility patterns. Each of these systems interacted with human and institutional actors but operated with a level of autonomy, adaptability, and embeddedness that went beyond passive instrumentation.

This challenges governance models that assume a clear separation between tools and actors. If governance is defined by influence over decisions, participation in framing problems, and affecting resource allocation (Renn, 2017: 52), then AI systems are increasingly fulfilling these criteria.

In this paper, we adopt an explicitly analytic-stakeholder stance: AI systems are not moral persons, nor bearers of rights or duties in the human sense; rather, they warrant treatment as stakeholders for purposes of governance analysis when (i) their outputs are routinely enrolled as obligatory passage points for public decisions, (ii) those outputs shape distributions of risk and resources, and (iii) human discretion is structurally conditioned by model design and data affordances. This position is consistent with ANT's account of distributed agency (Latour, 2005:72–73) and with contemporary regulatory architectures that govern AI as systems to be audited, explained, and constrained—without conferring personhood (Council of Europe, 2024; Regulation (EU) 2024/1689). In short, we treat AI as a non-human stakeholder in an analytical sense—an entity whose effective agency is institutionally produced and therefore must be institutionally governed (NIST, 2023; OMB, 2024; OECD, 2024).

Anticipatory Governance and the Shifting Stakeholder Landscape

The concept of anticipatory governance (Guston, 2010; Quay, 2010) highlights the need for forward-looking institutions capable of addressing emerging risks before they escalate. AI aligns with this vision by enabling predictive modeling, real-time risk detection, and adaptive responses. However, as noted in the literature, anticipatory governance must also engage with normative questions: Who has authority? Whose values guide the system? How is legitimacy maintained?

If AI systems become integral to anticipating and responding to urban risks, then they participate, albeit indirectly, in shaping the political contours of future cities. This raises profound governance challenges. Who audits the algorithms? How are ethical dilemmas resolved in opaque systems? These are not merely technical concerns; they are political questions about control, representation, and legitimacy.

Anticipatory governance increasingly operates through codified risk and accountability regimes. Three 2023–2024 instruments illustrate this trajectory and provide practical scaffolding for cities: NIST's AI Risk Management Framework (2023) translates anticipatory aims into lifecycle risk identification, measurement, and mitigation practices (NIST, 2023); the U.S. OMB memorandum (2024) requires agency-level AI governance, public inventories for safety-impacting uses, and minimum risk controls for systems affecting rights and safety (OMB, 2024); and the EU AI Act (2024) embeds ex-ante obligations for high-risk deployments, including documentation, human oversight, and conformity assessment. Together, these instruments operationalize anticipatory governance by hard-wiring foresight, monitoring, contestability, and learning into AI deployments that touch public values.

Political Participation Without Citizenship?

A provocative question thus arises: can AI be said to "participate" politically, even if it lacks agency in the human sense? Traditionally, political participation has required intentionality, voice, and accountability qualities that AI does not possess. Yet in practice, AI systems now affect who gets what, when, and how, according to Lasswell's (1936) classical definition of politics. If an AI system determines which neighborhoods receive flood warnings or how emergency services are dispatched, it is intervening in distributive and deliberative processes.

This has implications for democratic governance, particularly in resilient cities where inclusivity and legitimacy are foundational. Should AI systems be considered stakeholders in these systems? If so, what institutional mechanisms are required to ensure they are governed rather than governing?

Some scholars propose developing frameworks for “algorithmic accountability” and “explainable AI” (XAI) to ensure transparency and uphold public trust (Burrell, 2016: 10; Cowls et al., 2019: 5). Others advocate for algorithmic representation, the idea that AI systems should be subject to forms of representation, auditing, and contestation similar to those found in public institutions (Danaher, 2018: 639).

Democratic participation should mirror AI's points of leverage. Concretely, we argue for three participatory layers aligned with current law and practice. (i) Ex-ante impact transparency: before deployment, conduct and publish Fundamental Rights Impact Assessments (FRIA) for high-risk public-sector systems, identifying affected groups, foreseeable harms, and oversight measures (Regulation (EU) 2024/1689, Art. 27). (ii) Use-phase visibility: maintain public algorithm registers that describe purpose, data, oversight, and appeal channels—building on municipal precedents (Amsterdam/Helsinki) that translate technical systems into civic-readable accountability (City of Amsterdam, 2020). (iii) Civic contestability: provide notice, reasons, and accessible redress when automated outputs materially affect services or safety; pair these with periodic public reporting on errors, overrides, and distributional effects (OMB, 2024; UNGA, 2024). These devices transform AI's "political participation without citizenship" into participatory governance over AI, thereby preserving legitimacy when model-conditioned choices allocate risks and resources.

Empirical Reflections from the Case Studies

The empirical cases support this theoretical trajectory. In Calgary, AI-assisted planning tools shaped infrastructure investment priorities. In Copenhagen, energy optimization decisions were automated based on predictive analytics, eliminating the need for real-time human intervention. In Kansas City, AI-adjusted urban flows were informed by data from thousands of sensors.

In all three cases, AI systems:

- They were embedded in critical decision loops,
- Operated with degrees of autonomy,
- Influenced material outcomes for communities.

These characteristics resemble stakeholder behavior, even in the absence of a traditional agency.

However, these systems also operate in opaque ways. The decision rules and training data are often inaccessible to the public. This reinforces the "black box" dilemma described by Burrell (2016: 4): when algorithms cannot be understood, they cannot be held accountable. Thus, treating AI as a stakeholder requires more than conceptual acceptance; it demands normative frameworks for visibility, contestability, and auditability.

The cross-case implications become sharper under this lens. Calgary should align spatial-prioritization tooling with a FRIA-style template that discloses criteria for neighborhood ranking and links model outputs to deliberative budget forums (EP, 2024). Copenhagen can publish an algorithm register entry for its predictive building controls, including escalation/override protocols, retraining cadence, and performance audits mapped to recognized risk frameworks (NIST, 2023). Kansas City can institutionalize decision logs and publish corridor-level equity metrics, enabling external replication of observed signal plans and systematic review after incidents (OMB, 2024). Across all three, periodic post-deployment reviews should test whether operational gains come at the expense of transparency, due process, or equitable service distribution.

Toward a Governance Model that Includes Non-Human Actors

In light of these developments, resilient urban governance must evolve. Recognizing AI as a non-human stakeholder entails:

- Designing institutional checks and balances for algorithmic systems
- Ensuring transparency and explainability in high-stakes contexts
- Embedding ethical oversight in both public procurement and the deployment of AI tools
- Promoting human-AI collaboration rather than substitution

This does not mean AI should be "granted rights" or personhood. Instead, it means that AI systems, like corporate entities or institutional actors, should be included in governance analysis and subject to rules of accountability, transparency, and responsibility. The rise of AI in urban governance requires a paradigm shift. No longer mere instruments, AI systems shape decisions, mediate risks, and influence how cities adapt to crises—conceptualizing AI as a non-human stakeholder invites both theoretical innovation and institutional reform. It calls for cities to acknowledge the political dimensions of technology and to build governance systems that are not only smart but also legitimate, inclusive, and reflexive.

To consolidate these lessons, we propose a minimum governance package suitable for resilient-city contexts: (1) Registration—public algorithm/AI registers describing purpose, data, oversight, and appeal channels; (2) Ex-ante assessment—FRIA (public sector/high-risk) or AIA-style disclosures that name affected groups and mitigations; (3) Operational safeguards—documented human-in/on-the-loop thresholds, pre-defined escalation rights, and real-time decision logging; and (4) Monitoring & audits—periodic bias/fairness testing and performance audits with published summaries.. This package elevates AI from opaque instrumentation to governed infrastructure, preserving democratic legitimacy while enabling anticipatory performance.

Conclusion

The growing embeddedness of artificial intelligence in urban risk governance necessitates a comprehensive rethinking of policy design and institutional oversight. The integration of AI into decision-making processes, as illustrated by climate adaptation strategies in Calgary, energy optimization in Copenhagen, and mobility management in Kansas City, demonstrates that it not only processes data but also influences distributive outcomes and urban priorities (Evergreen, 2023; Pictet Asset Management, 2024; Viridis Initiative, 2023). Considering this, urban policymakers must develop regulatory mechanisms that reflect AI's operational autonomy and potential political impact.

First and foremost, cities should prioritize establishing accountability frameworks that ensure transparency and public oversight of AI systems. The opacity of many machine learning models, particularly those utilizing deep learning, poses a fundamental threat to democratic legitimacy (Burrell, 2016). Therefore, explainable AI (XAI) standards should become a cornerstone of public sector algorithm deployment, particularly in situations where systems influence high-stakes decisions, such as disaster response or infrastructure planning (Cowls et al., 2019; UNDRR, 2020).

In parallel, policymakers must address the normative vacuum surrounding AI's role in governance by advancing the concept of algorithmic representation. AI systems, much like institutional actors, should be auditable, contestable, and subjected to public deliberation. Some scholars suggest the formation of independent algorithm audit boards, tasked with evaluating the fairness, bias, and societal impact of these technologies (Danaher, 2018). Such bodies could act as ethical intermediaries in settings where direct democratic accountability is not feasible.

Furthermore, it is vital to promote human-AI collaboration rather than replacement. AI systems should serve as decision-support tools within hybrid governance frameworks, where human judgment is enhanced but not supplanted by computational efficiency (Guston, 2010: 434-436; Renn, 2017). Such arrangements are essential in anticipatory governance contexts, where the balance between speed and normative legitimacy is often delicate.

Finally, AI's participatory potential should not be overlooked. When deployed inclusively, AI can enhance citizen engagement through natural language processing tools, participatory dashboards, and real-time risk communication systems (UNDRR, 2020; Liu et al., 2023). These applications democratize access to knowledge and increase the responsiveness of public institutions, goals long championed by governance scholars and practitioners alike (Kara Yıldırım, 2018; Sobacı, 2007).

Altogether, these policy implications call for a deliberate and inclusive transformation of governance frameworks. AI may lack consciousness or intention, but its actions reverberate throughout the sociotechnical architectures of the modern city. Therefore, to safeguard democratic values in the age of algorithmic decision-making, urban institutions must move beyond treating AI as a neutral tool and begin addressing it as a governed entity, subject to ethical scrutiny, public values, and institutional design.

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APPENDIX

Table 1. Analytical Framework for Thematic Cross-Case Analysis

Research Question	Basic Theoretical Concept	Analytical Dimension	Empirical Indicators (Examples sought in sources such as policy documents, reports, etc.)
RQ1: Under what conditions do city-deployed AI systems exhibit agency-like effects in risk governance (problem framing, prioritization, and allocation)?	Agency (Actor-Network Theory)	Problem Framing and Prioritization	Definition of risks as 'AI-detectable' in policy documents; automated resource allocation rules described in technical reports; system dashboards that prioritize specific alerts or data streams.
RQ2: How does AI's embedding in socio-technical networks redistribute discretion, responsibility, and accountability among human and non-human actors?	Distributed Agency (ANT); Risk Governance	Discretion and Accountability Chains	Descriptions of human oversight protocols ('human-in-the-loop' vs. 'human-on-the-loop'); clauses defining liability in case of algorithmic error; media reports on system failures and subsequent institutional responses.
RQ3: What are the implications of such redistributions for core resilience functions (anticipation, preparedness, response, and learning)?	Anticipatory Governance; Resilience Functions (IRGC)	Anticipation, Preparation, and Learning	Use of predictive analytics for future scenarios (e.g., climate modeling in Calgary); real-time response protocols (e.g., traffic management in Kansas City); evidence of system updates or model retraining based on performance data.

Table 2. Comparative Analysis of AI Applications in Resilient Cities: Domains, Functions, Outcomes, Governance Implications, and Stakeholder Interaction

City	Application Domain	Role of AI	Outcomes	Governance Implications	Stakeholder Interaction
Calgary	Climate risk & infrastructure planning	Risk profiling; integration of environmental and community data	Informed planning decisions; enhanced community resilience	Make algorithmic criteria auditable; link model outputs to deliberative budget forums	Planners, utilities, and communities co-review risk maps; elected bodies set thresholds/guardrails
Copenhagen	Energy management	Real-time monitoring and optimization of public building systems	Reduced energy consumption; lower carbon footprint	Define override/escalation protocols; periodic model validation and performance audits	Facilities teams supervise vendor systems; sustainability offices track KPIs and report to councils
Kansas City	Urban mobility	Dynamic traffic signal control using real-time data	Decreased traffic congestion; improved air quality and commuter satisfaction	Maintain decision logs; fairness testing across corridors; incident-driven review loops	Traffic ops centers can override; residents and businesses engage via performance dashboards

Sources: Evergreen (2023); Pictet Asset Management (2024); Viridis Initiative (2023)